2004-09

Analysis of the Vertical Takeoff and landing Unmanned Aerial Vehicle (VTUAV) in small unti urban operations

Cason, Roman K.

Monterey, California. Naval Postgraduate School

NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

ANALYSIS OF THE VERTICAL TAKEOFF AND LANDING UNMANNED AERIAL VEHICLE (VTUAV) IN SMALL UNIT URBAN OPERATIONS

by

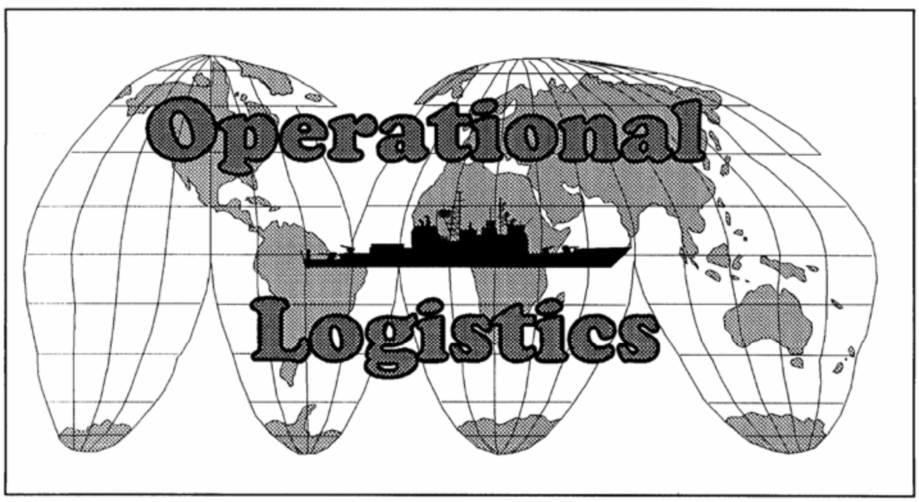
Roman K. Cason

September 2004

Thesis Advisor:	Susan M. Sanchez
Second Reader:	Paul J. Sanchez

Approved for public release; distribution is unlimited.

Amateurs discuss strategy, Professionals study logistics



REPORT DOCUMENTATION PAGE — *Form Approved OMB No. 0704-0188*

1. AGENCY USE ONLY *(Leave blank)*

2. REPORT DATE September 2004

3. REPORT TYPE AND DATES COVERED Master's Thesis

4. TITLE AND SUBTITLE: An Analysis of the Vertical Takeoff and Landing Unmanned Aerial Vehicle in Small Unit Urban Operations

5. FUNDING NUMBERS

6. AUTHOR(S) Roman K. Cason

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Naval Postgraduate School
Monterey, CA 93943-5000

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING /MONITORING AGENCY NAME(S) AND ADDRESS(ES)
N/A

10. SPONSORING/MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.

12a. DISTRIBUTION / AVAILABILITY STATEMENT
Approved for public release; distribution is unlimited

12b. DISTRIBUTION CODE

13. ABSTRACT (maximum 200 words)

The Marine Corps has recently embarked on the development of a Vertical Takeoff and Landing Unmanned Aerial Vehicle (VTUAV) to replace the aging Pioneer system. This thesis examines the critical elements this platform must possess in order to effectively support small units operating in urban environments. We address this issue by creating and exploring an agent-based simulation of a platoon conducting an urban patrol in a setting similar to those currently being encountered in Iraq. The platoon utilizes the VTUAV as an intelligence-gathering asset.

We use an efficient designed experiment to generate data from the simulation scenario, and then use multiple regression and regression trees to relate the UAV capabilities to the patrol's operational effectiveness. Our results suggest that the effectiveness of a VTUAV is greatly influenced by noise in the urban warfare environment. We use a loss function, along with the regression models, to identify UAV configurations that improve operational effectiveness yet are robust to uncertainties about civilian and insurgent behavior. The VTUAV must have high communication capability, as well as accurate sensing, in order to perform well across a range of environmental conditions.

14. SUBJECT TERMS Unmanned Aerial Vehicle, Agent-Based Models, MANA, Agent-Based Distillations, Latin Hypercube, Robust Design, Project Albert, Urban Warfare, Linear Regression

15. NUMBER OF PAGES 92

16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	UL

NSN 7540-01-280-5500

Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std. 239-18

THIS PAGE INTENTIONALLY LEFT BLANK

Approved for public release; distribution is unlimited.

ANALYSIS OF THE VERTICAL TAKEOFF AND LANDING UNMANNED AERIAL VEHICLE (VTUAV) IN SMALL UNIT URBAN OPERATIONS

Roman K. Cason
Captain, United States Marine Corps
B.S., Louisiana State University, 1994

Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

NAVAL POSTGRADUATE SCHOOL
September 2004

Author: Roman K. Cason

Approved by: Susan M. Sanchez
Thesis Advisor

Paul J. Sanchez
Second Reader

James N. Eagle
Chairman, Department of Operations Research

THIS PAGE INTENTIONALLY LEFT BLANK

ABSTRACT

The Marine Corps has recently embarked on the development of a Vertical Takeoff and Landing Unmanned Aerial Vehicle (VTUAV) to replace the aging Pioneer system. This thesis examines the critical elements this platform must possess in order to effectively support small units operating in urban environments. We address this issue by creating and exploring an agent-based simulation of a platoon conducting an urban patrol in a setting similar to those currently being encountered in Iraq. The platoon utilizes the VTUAV as an intelligence-gathering asset.

We use an efficient designed experiment to generate data from the simulation scenario, and then use multiple regression and regression trees to relate the UAV capabilities to the patrol's operational effectiveness. Our results suggest that the effectiveness of a VTUAV is greatly influenced by noise in the urban warfare environment. We use a loss function, along with the regression models, to identify UAV configurations that improve operational effectiveness yet are robust to uncertainties about civilian and insurgent behavior. The VTUAV must have high communication capability, as well as accurate sensing, in order to perform well across a range of environmental conditions.

THIS PAGE INTENTIONALLY LEFT BLANK

THESIS DISCLAIMER

The reader is cautioned that computer programs developed in this research may not have been exercised for all cases of interest. While every effort has been made within the time available to ensure that the programs are free of computational and logic errors, they cannot be considered validated. Any application of these programs without additional verification is at the risk of the user.

THIS PAGE INTENTIONALLY LEFT BLANK

TABLE OF CONTENTS

LIST OF FIGURES

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF TABLES

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF ACRONYMS AND ABBREVIATIONS

ABM	Agent Based Model
ER	Exchange Ratio
GCS	Ground Control Stations
GUI	Graphical User Interface
IED	Improvised Explosive Device
IF	Infrared Radar
LHC	Latin Hypercube
MAGTF	Marine Air Ground Task Force
MANA	Map Aware Non-uniform Automata
MCWP	Marine Corps Warfighting Publication
MOE	Measure of Effectiveness
MOOTW	Military Operations Other than War
MOUT	Military Operations on Urban Terrain
NEF	Naval Expeditionary Force
NOLHC	Nearly Orthogonal Latin Hypercube
OMFTS	Operational Maneuver from the Sea
ORD	Operational Requirements Document
R^2	Coefficient of Determination
ROE	Rules of Engagement
SA	Situational Awareness
SAR	Synthetic Aperture Radar
SASO	Stability and Support Operations
SAW	Squad Automatic Weapon
STOM	Ship to Objective Maneuver
UAV	Unmanned Aerial Vehicle
VTUAV	Vertical Takeoff and Landing Unmanned Aerial Vehicle

THIS PAGE INTENTIONALLY LEFT BLANK

ACKNOWLEDGMENTS

I would like to thank my thesis advisor Professor Susan Sanchez for her patience, guidance, and inspiration during this process. Your knowledge and enthusiasm has made this a rewarding experience. I would also like to thank the many other professors in the Operations Research department who have made this accomplishment possible.

I would also like the students whom I have shared the last two years with here in the OR curriculum. Although too many to mention by name, you have all given up a piece of your time in order to help a Cajun boy from Louisiana accomplish this goal.

Most importantly I would like to thank my family. Lucy, you have given me your full support and have provided me the encouragement and inspiration I needed when I needed it. Addie, your smile and laugh make everyday a gift. I love and thank you both.

THIS PAGE INTENTIONALLY LEFT BLANK

EXECUTIVE SUMMARY

Although major combat in Iraq has ended, the task of securing the nation is far from complete. The military forces in Iraq have the difficult task of conducting stability and support operations (SASO) to root out any insurgent and terrorist activities in order for democracy to take hold. In order to win the hearts and minds of the people, and stabilize the fledgling democracy in Iraq, the U.S. troops must focus on the political and population centers of Iraq. Unfortunately, it is in this urban environment that military operations can exact a heavy toll. Urban areas allow insurgent groups to inflict high casualties while avoiding decisive engagements. Urban areas also offer a target-rich environment for terrorist tactics, such as the kidnapping of civilian contractors, diplomats, and aid workers, as well as the use of improvised explosive devices (IEDs). Due to the success of these tactics, the U.S. must find better ways to utilize its technological and firepower advantages.

During the course of the last year, the Marine Corps has introduced many technological enhancements in order to give our troops the best possible advantages. In addition to ground equipment improvements, the Marine Corps is currently seeking to replace the aging Pioneer Unmanned Aerial Vehicle (UAV) with a more capable platform better suited for an expeditionary force. This new UAV will be equipped with Vertical Takeoff and Landing (VTOL) capability. With this new capability the Marine Corps will have greater flexibility in the areas that the UAV could be employed. The new VTUAV will able to span the spectrum from low to high intensity combat, including urban warfare. Because of the dense chaos of urban warfare, we must examine the capabilities that a UAV must possess in order for U.S. forces to exploit this technological advantage in such an environment.

In this thesis, we examine the impact of providing a small infantry unit with a UAV during urban patrolling operations. We create a simulation model of this scenario using an agent-based modeling platform called *Map Aware Non-uniform Automata* (MANA). This scenario is modeled off of the current situation our forces are encountering in Iraqi urban areas. The platoon has one UAV that is used as an

intelligence gathering asset. Enemy forces operate in small groups and utilize the cover and concealment of the urban landscape. The insurgent forces also exercise influence over the local populace, fueling anti-American sentiment.

We gain insights from this simulation by using the technique known as Data Farming. Data Farming involves generating a very large number of data points from simple computer models, based on a wide range of model inputs, in order to explore the models' behavior. These inputs include UAV capabilities: its sweep width, observation cover, and speed, along with communication reliability, latency, and accuracy. Characteristics of the Iraqi civilians and insurgents are also varied over broad ranges. We use an efficient experimental design approach to specify the combination of model inputs. Even so, over 40,000 simulations are run to provide data for our analysis.

We use a robust design approach to analyze the results. This approach is based on the idea that a system should be relatively insensitive to variations or noise in the environment. Robust solutions are particularly appealing for combat systems. In the combat environment, military systems are constantly affected by uncontrollable sources of variation. This thesis is intended to be a preliminary study of the factors that contribute to the success of the VTUAV in support of a small unit conducting urban operations. Exact numerical results of this study should not be taken as a literal translation into real world numbers. It is the insights, not the numbers, that are the focus of our investigation.

Based on the robust design philosophy our thesis work suggests the following results:

- The hostility of the civilian population plays an important role in urban combat. If civilian hostilities are high, a more sophisticated UAV might be necessary. In environments with friendlier populations, other less sophisticated intelligence assets might be sufficient to accomplish the mission.
- A platform that has very reliable communication capability and very accurate sensing capability is best suited for the range of environmental conditions modeled. These two factors were the most dominant in providing favorable results.

- The aggressiveness of the blue force has an impact on the mean exchange ratio. In situations where commanders cannot tolerate the possibility of high losses, a less aggressive force that relies more heavily on the UAV for situational awareness and enemy engagements might be more appropriate.
- The ‘best’ decision resulting from the robust design approach is different than the decision that would have resulted by only using mean performance. The resulting system is more insensitive to uncontrollable sources of variation in the combat environment.
- By using intelligent design techniques, we are able to capture the essence of the problem by using relatively few data points.
- The data farming environment, coupled with agent-based models, provides an excellent framework for gaining insights into interesting interactions in combat modeling.

A UAV that has reliable communication and accurate sensing capability will work best across a broad range of environments. If we have some information about the environment such as the civilian hostility, we may be able to use a less sophisticated UAV and still operate effectively. Finally, the aggressiveness of the blue forces plays a key role in achieving higher exchange ratios, but it can also result in higher risks. If the potential for high losses can not be tolerated, the blue force should rely more heavily on the intelligence gathering and targeting capabilities of the UAV.

THIS PAGE INTENTIONALLY LEFT BLANK

I. INTRODUCTION

Intelligence is imperative to success in urban warfare. "Maneuver warfare requires a firm focus on the enemy" (MCDP 2, Intelligence). Few subsequent tactical changes can overcome the far-reaching impact of a major intelligence error.

MCWP 3-35.3
Military Operations in Urban Terrain (MOUT)

A. MOTIVATION

In the three years since the attack on the U.S. on September 11, 2001, the U.S. military has removed the ruling government from two nations and has begun the process of establishing democratic governments in both. In Iraq the military forces have the difficult task of conducting stability and support operations (SASO) to root out any insurgent and terrorist activities in order for democracy to take hold. They also must win the support of the people through various humanitarian projects and daily interaction. In order to win the hearts and minds of the people and stabilize the fledgling democracy in Iraq, the U.S. troops must focus on the political and population centers of Iraq. Unfortunately, it is in this urban environment that military operations can exact a heavy toll. Utilizing the advantages of the urban terrain, insurgents have begun a campaign of terror aimed at the U.S., its coalition partners, and even Iraqi citizens. With its superior combat power and technological advantage, the U.S. forces toppled Saddam Hussein's regime in just three weeks. However, stabilization efforts are still ongoing over one year later.

Urban areas allow insurgent groups to inflict high casualties while avoiding decisive engagements. Urban areas also offer a target-rich environment for terrorist tactics, such as the kidnapping of civilian contractors, diplomats, and aid workers, as well as the use of improvised explosive devices (IEDs). Due to the success of these tactics, the U.S. must find better ways to utilize its technological and firepower advantages. During the course of the last year the Marine Corps has introduced many technological enhancements in order to give our troops the best possible advantages. In addition to ground equipment improvements, the Marine Corps is currently seeking to replace the aging Pioneer Unmanned Aerial Vehicle (UAV) with a more capable platform better suited for an expeditionary force. Because of the dense chaos of urban warfare, we must examine the capabilities that a UAV must possess in order for U.S. forces to exploit this technological advantage in such an environment.

B. PURPOSE

The purpose of this thesis is to utilize an agent-based model (ABM) to develop a simulation representing a small unit urban infantry patrolling operation utilizing a UAV. The simulation will be used to identify important factors, primarily related to the UAV, that are vital to mission success.

C. BACKGROUND

As part of naval expeditionary forces (NEFs), the Marine air-ground task forces (MAGTFs) are forward deployed for rapid crisis response. As a rapid response force, Marines may be employed in a wide range of military operations. Studies have shown that 75% of politically significant urban areas, other than allied or former Warsaw Pact territories, are located within 150 miles of a coastline. As a rapidly deployable naval force the Marines must be prepared to operate in these large urban areas.

Historically, the attacker usually wins in urban battles. This statistic may be attributable to the fact that urban warfare extracts a heavy toll on the attacker, causing him to attack only when he has a decisive advantage—not only in numbers, but also in other factors such as intelligence and superior training and equipment.

> *Regardless of the size or quality of defensive forces, the defender usually extracts large costs from the attacker in time, resources, and casualties.* [MCWP 3-35.3, April 1998]

Military operations in urban environments have historically involved small infantry units and have been casualty intensive affairs.

Current operations in Iraq demonstrate the difficulties of patrolling in an urban environment. Insurgents are able to blend into the local populace, containing many who are sympathetic to their cause. Using IEDs and taking hostages are some of the tactics being used against U.S. Forces. In Ramadi, a city of about 400,000 on the Euphrates

River west of Baghdad, Marines are currently conducting security patrols looking for weapons and insurgents while still trying to win the hearts and minds of the local populace. During routine patrols in early April 2004, the city erupted in a series of coordinated ambushes by hundreds of Iraqis shooting at Marines from alleys, behind windows and doors, and out in the street.

> *When this was taking place, two hours into it, everyone and their mother was shooting at us.*
>
> Staff Sgt. Damien Rodriguez
> Regarding the fighting in Ramadi, Iraq April 6, 2004

It is this type of fighting that has served as the basis for development of the scenario examined in this thesis.

D. UNMANNED AERIAL VEHICLES BACKGROUND

A Marine Corps analysis on the Russian war in Chechnya stated that UAVs were used extensively and effectively in the urban environment [FM 3-06.11, 2002]. The use of UAVs in military operations has stretched for nearly one hundred years. From the early years of flight, through the Vietnam War, to today, unmanned surveillance continues to play an important role in military operations. Because there are many different types of unmanned aircraft, we use the definition of a UAV from Joint Publication 1-02:

> *A powered, aerial vehicle that does not carry a human operator, uses aerodynamic forces to provide vehicle lift, can fly autonomously or be piloted remotely, can be expendable or recoverable, and can carry a lethal or non-lethal payload. Ballistic or semi ballistic vehicles, cruise missiles, and artillery projectiles are not considered unmanned aerial vehicles.*

With today's technology, the UAV is far more capable and sophisticated than those of just a few years ago. As technological advances continue, the UAVs of tomorrow will possess capabilities that will allow military commanders to receive large amounts of relevant information more quickly and more reliably than is possible using the UAVs of today.

America's first version of a modern UAV was the Lightning Bug. It was used as a targeting decoy during the Vietnam War. During the war it was outfitted with primitive computers and cameras for surveillance, but limitations in its navigation system meant it could not be reliably deployed. It continues to hold the record as the most expensive drone ever built by the U.S. In today's dollars it would cost $4.5 billion [*Spies That Fly*, July 2004].

The next major advancement in UAVs occurred in 1982 during the Arab/Israeli War in southern Lebanon. Initially, the Israeli Air Force sustained significant losses due to the Soviet supplied anti-air capability. In response to these losses, the Israelis developed a UAV to act as a decoy. This propeller-driven UAV had no firepower, and was controlled from the ground with radio signals. It was slow, unsophisticated, and had limited range, but it carried signal generators that gave off the radar signature of a much bigger plane. By sending in a wave of these UAVs before the manned fighters, the Israelis caused the Syrians to turn on their radar. This allowed the Israeli fighters to launch anti-radiation missiles and destroy the radars. Later, the Israelis would equip these UAVs with cameras for surveillance operations [*Spies That Fly*, July 2004].

Motivated by the success of the Israelis and such acts as the bombing of the Marine barracks in Lebanon, the U.S. began to develop its own UAV (called the Pioneer) modeled after that of Israel. The Pioneer first saw action during Operation Desert Storm. Capable of staying aloft for hours, it was assigned to battle ships for targeting purposes. It was launched from the ship with a rocket-propelled catapult and retrieved in a cargo net. The Pioneer enabled the U.S. to receive real-time target damage assessment and reduced the need for human eyes on the target. Iraqi soldiers actually tried to surrender to these UAVs because they knew that if they heard a drone that bombs would usually follow [*Spies That Fly*, July 2004]. The Pioneer had a limited range due to its line of sight communications requirement. This challenge was soon answered with the introduction of the next U.S. UAV, called the Predator.

The Predator was the first UAV that could receive signals from satellites and therefore know its position at all times. It could stay aloft for 40 hours. It first saw service in 1995 over Bosnia [*Spies That Fly*, July 2004]. It was equipped with a camera, infrared radar (IR), Synthetic Aperture Radar (SAR), and a laser designator for targeting. The Predator is good at keeping track of a target, but its narrow field of view limits its ability to find a target unless the location is known.

The largest and most sophisticated U.S. UAV is the Global Hawk. It was used in Afghanistan while still in the flight test stage. It is jet powered and can cruise at an altitude of 65,000 feet [*Spies That Fly*, July 2004]. The Global Hawk is programmed from takeoff to touchdown and does not have the capability of being piloted from the ground. It is a pure surveillance platform, carrying no weapons payload. It recently completed a flight from California to Australia without refueling [*Spies That Fly*, July 2004]. The Global Hawk is capable of surveying a much larger area than the Pioneer, but at $40 million apiece it costs substantially more than any other current UAV.

The Marine Corps currently possesses two UAVs that are both used for surveillance purposes only: the Pioneer and the Dragon Eye. The Dragon Eye is a man-packed, propeller-driven UAV. It is equipped with a small camera, has a short range and flying time, and is used for over-the-hill reconnaissance only. The Marine Corps has embarked on a program to replace the Pioneer with a Vertical Takeoff and Landing UAV (VTUAV). The VTUAV is expected to provide support to operations spanning the spectrum of Military Operations Other Than War (MOOTW) to a large intensity conflict [*Operational Requirements Document (ORD) for the VTUAV*]. Some of the limitations of Pioneer include its limited shipboard compatibility, obsolete Ground Control Stations (GCS) and inadequate speed. The VTUAV will provide the capabilities to support the Marine Corps concepts of Operational Maneuver From the Sea (OMFTS) and Ship to Objective Maneuver (STOM). The capabilities of the VTUAV will include: target acquisition, surveillance, reconnaissance, target designation, communications and data relay, electronic warfare, and delivery of remote sensors and non-lethal weapons [*ORD for the VTUAV*]. The VTUAV will be an organic asset of the Marine Air Ground Task Force (MAGTF) Commander. Current fielding projections have the VTUAV available to the FMF by FY08 [*ORD for the VTUAV*].

E. SCOPE

In an urban combat scenario it is possible to examine hundreds of factors that might contribute to mission success. The introduction of an intelligence-gathering asset such as a UAV to this environment adds to the complexity of the analysis. In order to conduct a practical examination of issues pertinent to the development and use of the VTUAV in conjunction with small unit urban operations, this thesis will adhere to the following plan for analysis:

- Review urban warfare tactics.
- Understand potential enemy tactics and courses of action.
- Identify measures of effectiveness.
- Explain the capabilities and limitations of the modeling tool.
- Explain the development of the simulation scenario.
- Discuss data farming and its application to the urban patrolling model.
- Analyze the data from our simulation runs and fit models to the output.
- Examine the results of our analysis as it pertains to urban patrolling with the VTUAV.

F. AGENT-BASED MODELS

This thesis will gain insights to questions by using the technique known as Data Farming. Data Farming is a method that generates a very large number of data points from simple computer models, based on a wide range of model inputs. The analyzed results can yield surprises, a better understanding of the model performance, and interesting outcomes. The Marine Corps Warfighting Laboratory's Project Albert has provided the necessary infrastructure for this research capability to the Marine Corps.

Project Albert's Data Farming approach is achieved through the use of agent-based models or distillations. Agent-based models have entities that are controlled by decision-making algorithms, enabling the analyst to examine how agents interact with one another in potentially interesting and non-linear ways. These are simple models that, when coupled with high performance computing, can generate potentially millions of data points for analysis. The agent-based modeling platform used in this thesis is *Map Aware Non-uniform Automata* (MANA). MANA was developed by the New Zealand Defence Technology Agency and was inspired by the work of Andy Ilanchinski and others using agent based models [Galligan et al.,2004]. MANA examines the interactions among agents that have their own personality traits and are able to move autonomously. The parameters for the agents fall into four basic types: (1) personality, (2) movement, (3) capabilities, and (4) movement constraints [Galligan et al., 2004].

By creating agents in MANA and varying these four types of parameters we can examine a wide range of behaviors. Of particular interest are the levels of several parameters or factors that potentially lead to interesting and/or unexpected results. Additionally, the way agents behave with one another, towards the enemy, with civilians and the VTUAV could also produce interesting insight into the scenario.

Once the scenario has been created in MANA and data have been generated, we can apply regression and other data analysis techniques to gain a better understanding of the interactions between the factors and provide a glimpse of the potential trade space for decision makers.

THIS PAGE INTENTIONALLY LEFT BLANK

II. MODEL DESCRIPTION AND DEVELOPMENT

A. SOME DOCTRINAL PRINCIPLES OF MOUT

The study of modern urban battles has resulted in some key insights into the major factors of urban combat. MCWP 3-35.3 [April, 1998] lists a few of these insights as the following:

- MOUT is infantry intensive;
- A tactical battle may have far-reaching implications, with operational and possibly strategic repercussions;
- Intelligence is imperative to success;
- Surprise is a combat multiplier;
- As force ratio increases in favor of the attacker, combat duration decreases;
- Urban warfare is time consuming; and
- Attack of an urban area is costly to the attacker in terms of resources and casualties.

Because of the nature of urban terrain, units often become separated and isolated. This forces the fighting to become a series of small-unit actions. When fighting unconventional forces in MOUT, our forces will usually be operating under restrictive rules of engagement (ROE). Insurgent forces will exploit our ROE and use the local population to their advantage when developing their defensive plan.

The preferred method of advancing along city streets is the double column. This allows 360 degrees of security and mutual support as shown in Figure 1.

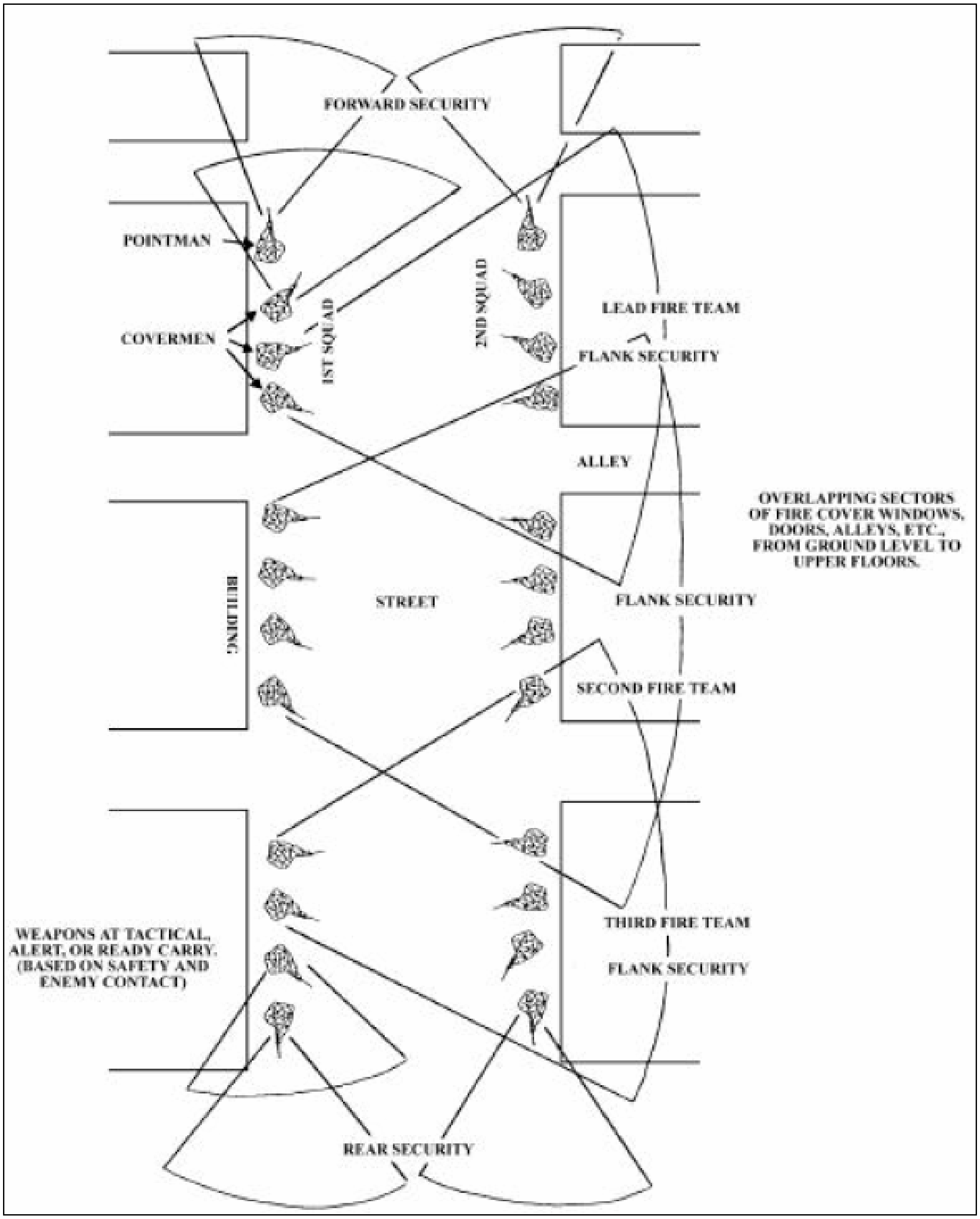


Figure 1. Patrolling Along an Urban Street [from MCWP 3-35.3, April 1998].

During a patrol, enemy contact is possible even if an area is deemed secure. If an enemy is engaged, the patrol's preferred choice should be to return fire immediately and conduct a hasty clearing of an adjacent structure in order to seek cover. This allows the

Marines to better acquire the enemy's position and to deliver well-aimed shots in order to use their firepower more effectively.

The nature of combat in urban areas affects the employment of weapon systems. Engagement areas are usually close in MOUT. According to MCWP 3-31,

> *Studies and historical analyses have shown that only 5 percent of all targets are more than 100 meters away. About 90 percent of all targets are located 50 meters or less from the identifying Marine. Few personnel targets will be visible beyond 50 meters, and most occur at 35 meters are less.*

The M16 rifle and M249 Squad Automatic Weapon (SAW) are the most frequently used weapons in urban areas primarily because these make up the chief firepower of the infantry platoon, but also because strict ROE and the fear of collateral damage prevent the use of indirect fire.

B. SMALL UNIT URBAN OPERATIONS SCENARIO

This analysis focuses on an infantry platoon conducting patrolling operations in an urban environment. The situation is modeled off of the current situation our forces are encountering in Iraqi urban areas. The mission of the patrol is to neutralize insurgents who are operating in the area, as well as to provide a presence to the local populace. The platoon consists of 39 members armed with small arms. They are supported by one UAV providing intelligence updates on possible enemy locations that is also capable of providing observational cover if the enemy engages the platoon. The situation in the city is tense and the citizens are not happy with the presence of U.S. troops. Many citizens are sympathetic to the insurgents and will aid them in certain situations. By using the urban terrain to their advantage, the insurgents operate in small units and avoid large-scale engagements. Using the cover and concealment afforded to them by the buildings, they will usually only initiate the engagement when they have the advantage of surprise. The insurgents operate as loosely organized irregular units with the ability to blend in with the local population, but because of their desire to make a political statement and influence the local citizens, they also have a desire to make their presence known.

C. MANA

All models are wrong, but some are useful.

George Box

As explained in Chapter I, we chose MANA as the platform for exploring this scenario. Much of the information that follows is taken from the April 2004 version 3.0.35 user's manual [Galligan et al., 2004]. MANA was developed because of a frustration with other more complex, physics based models that were available. While highly detailed, these models were unable to capture other intangible factors of combat—such as human behavior—which can be critical determinants of battle outcomes. The developers offer this advice for those using MANA:

> *There must be a clear idea of which aspect of warfare the scenario is addressing, and what the entities are trying to do. Though such an approach may seem pre-potted, the non-linear nature of the model ensures that, regardless of the modeller's preconception, a startlingly large number of outcomes are possible. Such a range of outcomes is characteristic of complex adaptive systems, and occurs even with quite simple rules of behaviour [Galligan et al, 2004].*

It is this range of possible outcomes that is of interest to decision makers. With MANA's user's manual and Graphical User Interface (GUI) it is relatively simple to build a scenario in a short amount of time.

D. MODELING OUR SCENARIO IN MANA

This section focuses on how our scenario's battlefield and agents were created in MANA. Screen shots are shown to aid the reader in understanding model development process.

1. Battlefield Development

The MANA battlefield is made up of grids that can range from 50 to 1000 pixels (or cells) on a side. The default terrain is a 200 x 200 grid. Our model uses a 1000 x 1000 design, which allows for the highest resolution. Each cell can be occupied by a single live entity. The map file is based on a standard Windows bitmap and different colors have an affect on an agents' ability to shoot, move, or communicate. MANA has preset terrains for its default battlefield, but the user can create additional terrains to provide cover and concealment, impede or facilitate movement and communication, or act as barriers. Figure 2 shows the Scenario Map Editor where changes can be made to the terrain.

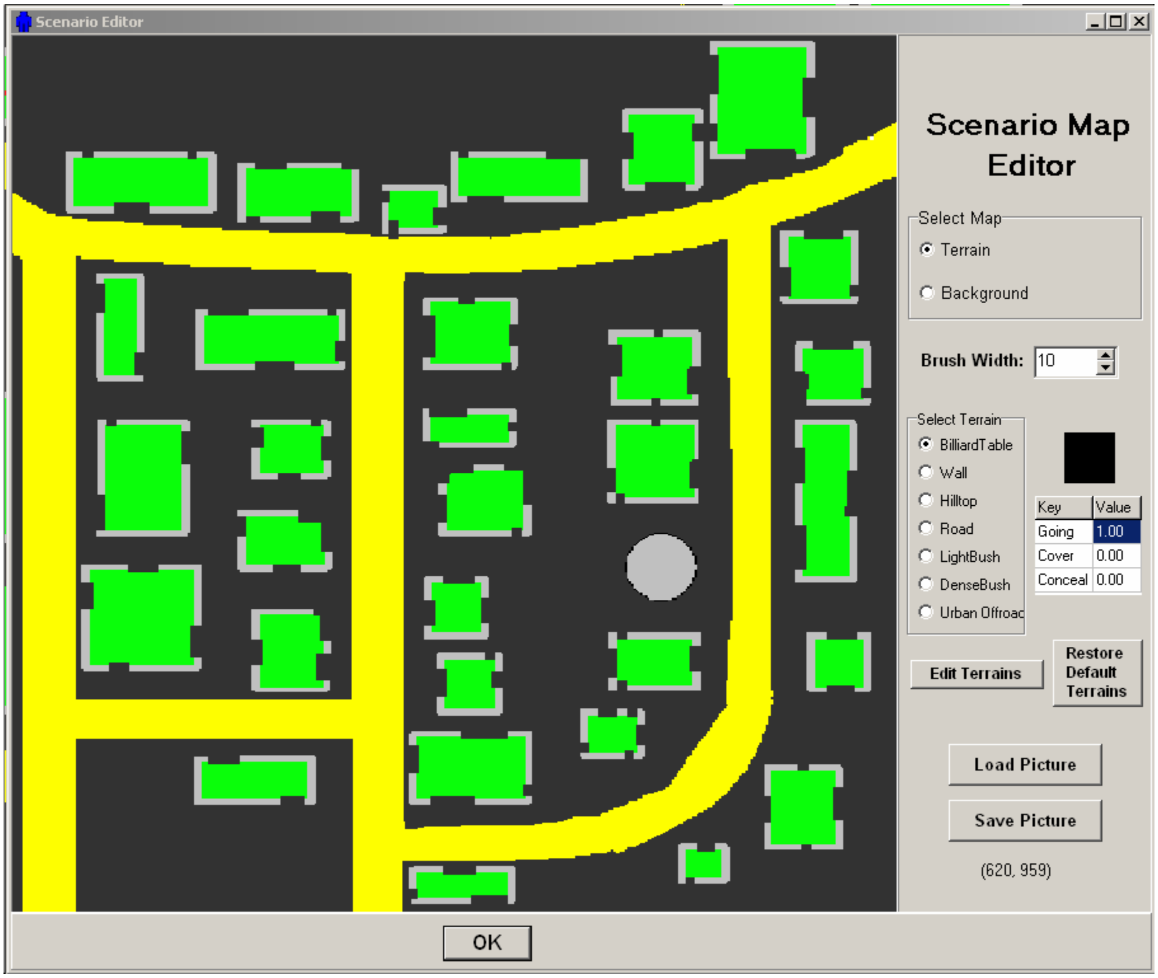


Figure 2. Scenario Editor.

2. Creating MANA Agents

In MANA a group of agents of any size (1-1000) is known as a squad. These squads have the same properties and can change between states as a group or individually. States are a set of values that determine the agents' behavior. This ability of agents to change their behavior based on a stimulus is a key component to modeling combat behavior. The squads created for this scenario are listed in Table 1.

Squad #	Squad Name	Allegiance	# of Agents	Description	Icon
1	Blue Squad 1	Blue	19	Infantry w/M16	Blue Soldier
2	UAV	Blue	1	UAV	Blue Airplane
3	Civilians	Neutral	90	Unhappy with U.S. Occupation	Yellow Person
4	IED	Red	1	Improvised Explosive Device	Red Cross
5	IED Observer	Red	1	Needed to detonate IED	Red Soldier in Prone
6	Red Squad 1	Red	3	Insurgents w/AK 47	Red Soldier
7	Red Squad 2	Red	3	Insurgents w/AK 47	Red Soldier
8	Red Squad 3	Red	3	Insurgents w/AK 47	Red Soldier
9	Red Squad 4	Red	3	Insurgents w/AK 47	Red Soldier
10	Red Squad 5	Red	3	Insurgents w/AK 47	Red Soldier
11	Red Squad 6	Red	3	Insurgents w/AK 47	Red Soldier
12	Blue Squad 2	Blue	19	Infantry w/M16	Blue Soldier
13	Red Squad 7	Red	3	Insurgents w/AK 47	Red Soldier
14	Red Squad 8	Red	3	Insurgents w/AK 47	Red Soldier
15	Red Squad 9	Red	3	Insurgents w/AK 47	Red Soldier

Table 1. Urban Patrol Squads

Squads can be guided through the scenario by a series of waypoints designated by the user. Their propensity to go to a waypoint is determined by the user via the personality settings of each squad, which we describe shortly.

The squad’s organic situational awareness (SA) and inorganic SA are important aspects of modeling information and communication on the battlefield. Whenever a squad member sees or detects another entity on the battlefield, this detection is transmitted to other members of the squad and stored in memory for a user-specified number of time steps. This allows the squad to have a collective picture of the battlefield and make decisions based on their personality weightings. Important to this scenario are the squads' inorganic SA. Inorganic SA is information passed to one squad by another squad. Like the squad's organic SA, the inorganic SA is stored in memory for a user-specified number of time steps. This feature allows the user to determine the importance of the age of information when making decisions. In the Inorganic SA Tab (Figure 3) we see that the user has the ability to vary certain factors that pertain to the communication aspects of passing information over a communication net. Accuracy, reliability, and latency are just of few of the parameters than can be varied.

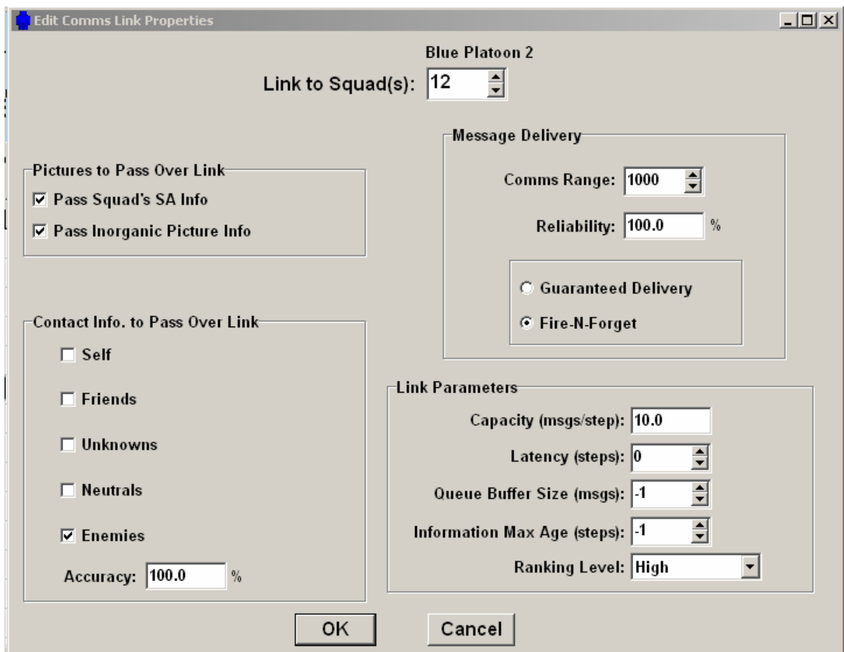


Figure 3. Inorganic SA Communication Properties.

A squad's current organic (internally generated) or inorganic SA can be viewed at anytime by selecting the appropriate SA from the view menu, as seen in Figure 4. Figure 4 displays the information being passed to the squad via the communications link of other designated squads. In our scenario the inorganic SA that the blue squad is receiving is from the UAV. Different colored boxes are displayed around different red icons. The yellow boxes indicate the UAV has detected a hostile civilian and the grey boxes indicate an insurgent detection. This information is passed to Squad 1 and displayed in Figure 4.

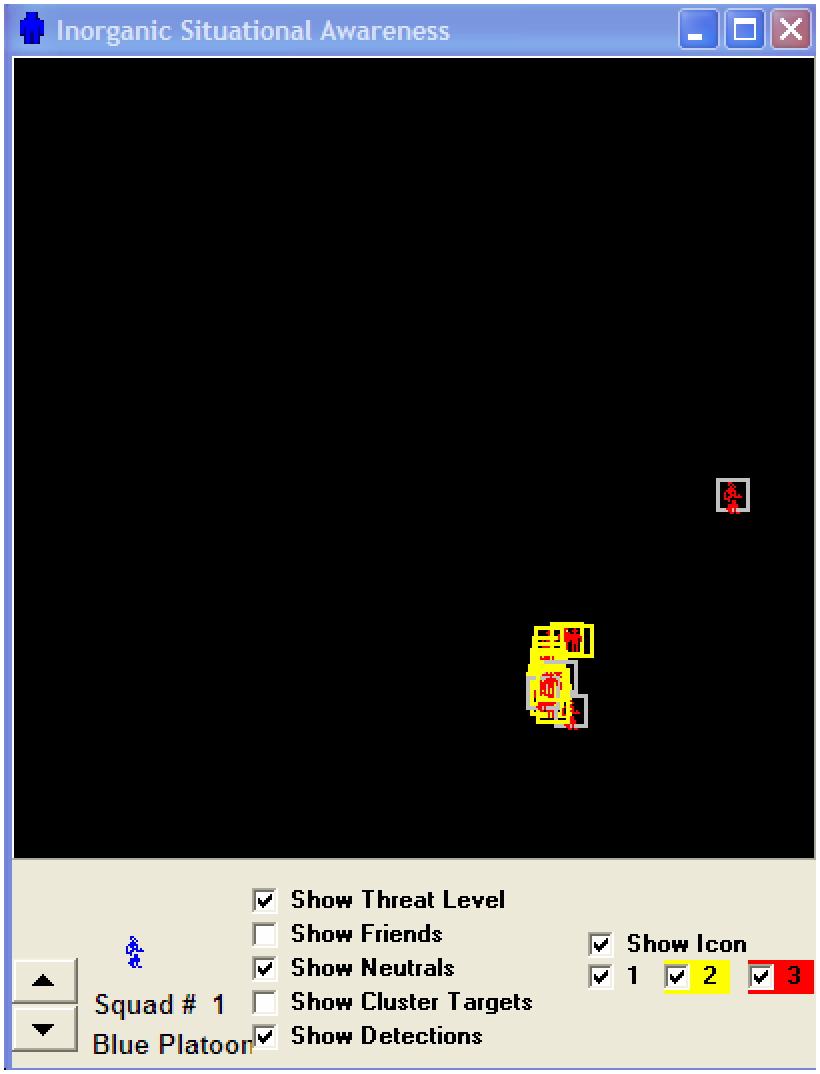


Figure 4. Squad Inorganic SA (Best Viewed in Color).

3. The Urban Patrol Scenario

Figure 5 displays a screenshot of the initial condition of the scenario for this analysis. The terrain is an urban environment with buildings, roads, alleys and structures. This map is actually modeled off of the MOUT training facility at Ft. Polk, Louisiana. The colors of the map represent various structures and each has unique cover and concealment attributes as well as an effect on squad movement. Yellow represents a major street. It offers ease of movement but no cover and concealment. Grey areas are walls or other solid structures. These areas offer good cover but entities are unable to pass through or over them. The light green areas represent the interior of buildings.

These areas offer good concealment and restrict movement. The black area of the map is representative of off-road urban terrain such as alleys, sidewalks and small streets. These areas offer little cover and concealment, while movement is only slightly more restrictive than that of major streets.

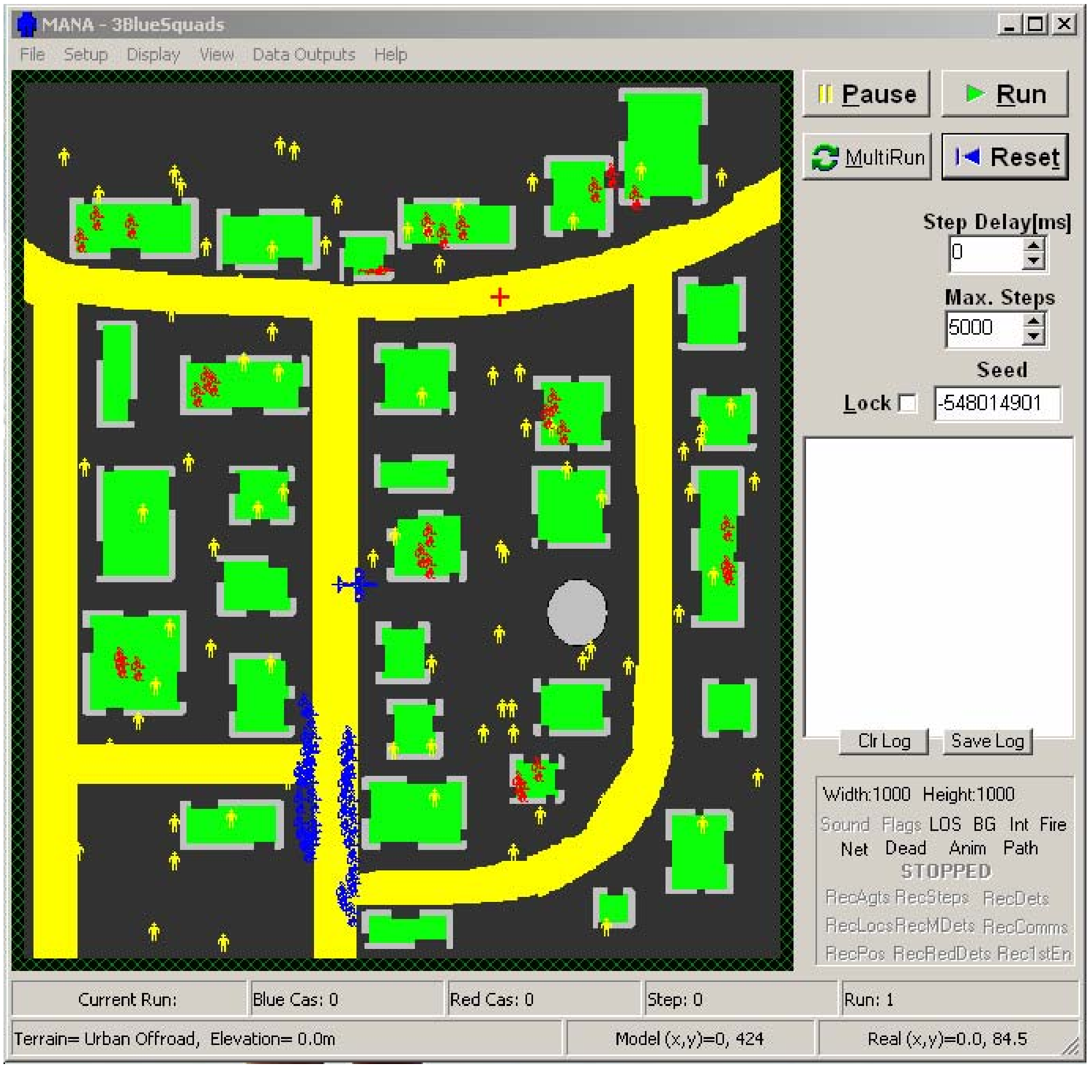


Figure 5. Urban Patrol Scenario (Best Viewed in Color).

The blue patrol starts at the bottom center of the map and proceeds north through the city following a series of waypoints. The blue platoon consists of two squads totaling 39 agents. The blue UAV will provide intelligence to the patrol by conducting a search of the city utilizing an alternating lawnmower search pattern. The UAV can be dynamically re-tasked, represented by a state change, to provide observation cover should the patrol encounter enemy agents along the patrol route. Following doctrine, the two squads move in parallel to one another along the outer edges of the street. Barring any enemy contact the platoon has a propensity to simply move from waypoint to waypoint. Once the squad makes contact with the enemy it will first seek cover and then proceed to engage the red agents, again following MOUT doctrine. If the patrol is not engaged with the enemy and the UAV detects and transmits enemy contact to the patrol, then the patrol will have a propensity to move towards the UAV contact to engage.

There are ten squads of insurgents, represented on the map as red soldiers: nine squads of three agents each, and one squad with one agent. The insurgents have a tendency to remain inside buildings, where they are difficult for the UAV to detect, until they see the blue patrol. Insurgents occupying the interior of a building or engaging blue forces from windows have a lower probability of detection than those engaging in the open. This lower probability of detection is represented in MANA by higher stealth settings for the red agents. Once the red agents spot the blue patrol, they then begin to move and engage, resulting in decreased stealth and increased probability of detection. The enemy IED is represented by a red cross. An observer, represented by a red soldier in the prone position, controls the IED. If this observer notices that blue soldiers are within range of the IED, he will arm the device. If the observer is killed prior to arming, the device is disabled. The IED can only be armed if the observer has a clear line of site to the device. In order to represent randomness in the IED's reliability, the observer's position is randomly generated so that it will not have a clear line of site to the IED for each run.

Neutrals are represented as yellow figures on the map. Their initial placements and movements are both random. If they come in close contact with an insurgent, they may undergo a state change and become hostile to the blue forces for a period of time. This state change is represented on the map by the figure changing colors from yellow to red.

4. Squad Personalities

The Squad Personalities screen, shown in Figure 6, is the method MANA uses for establishing an agent's characteristics for certain types of actions. The various weightings given under agent, squad or inorganic SA affect the squads' propensity towards certain actions. These ordinal weightings can vary from –100 to 100. For example, an agent with a weighting of 100 for *Enemies* will have a strong desire to move toward enemy agents, while an agent with a weighting of –100 will have a strong desire to move away from enemy agents. It is worth mentioning that it is not necessary for an entity to have a weighting of 100 to have a strong desire to move toward the enemy. As long as the *Enemies* weighting is positive and greater than any of the other personality weighting, the entity's strongest desire will be to move toward enemy agents. In Figure 6 we see the personalities of the blue platoon in its default state (indicated by the highlighted box at the top of the *Trigger State* window shown on the right-hand-side of the screen). The greatest influence on the agents is the detection of an enemy agent via the blue agent or blue squad organic SA. This propensity to engage the red agents is in keeping with the mission of the patrol. Because the weighting of the squad SA is greater than inorganic SA, the squad will not break contact with an enemy to seek other enemy reported elsewhere by the UAV. If the patrol is not engaged and receives inorganic SA from the UAV, it will have a propensity to move towards the inorganic enemy contact.

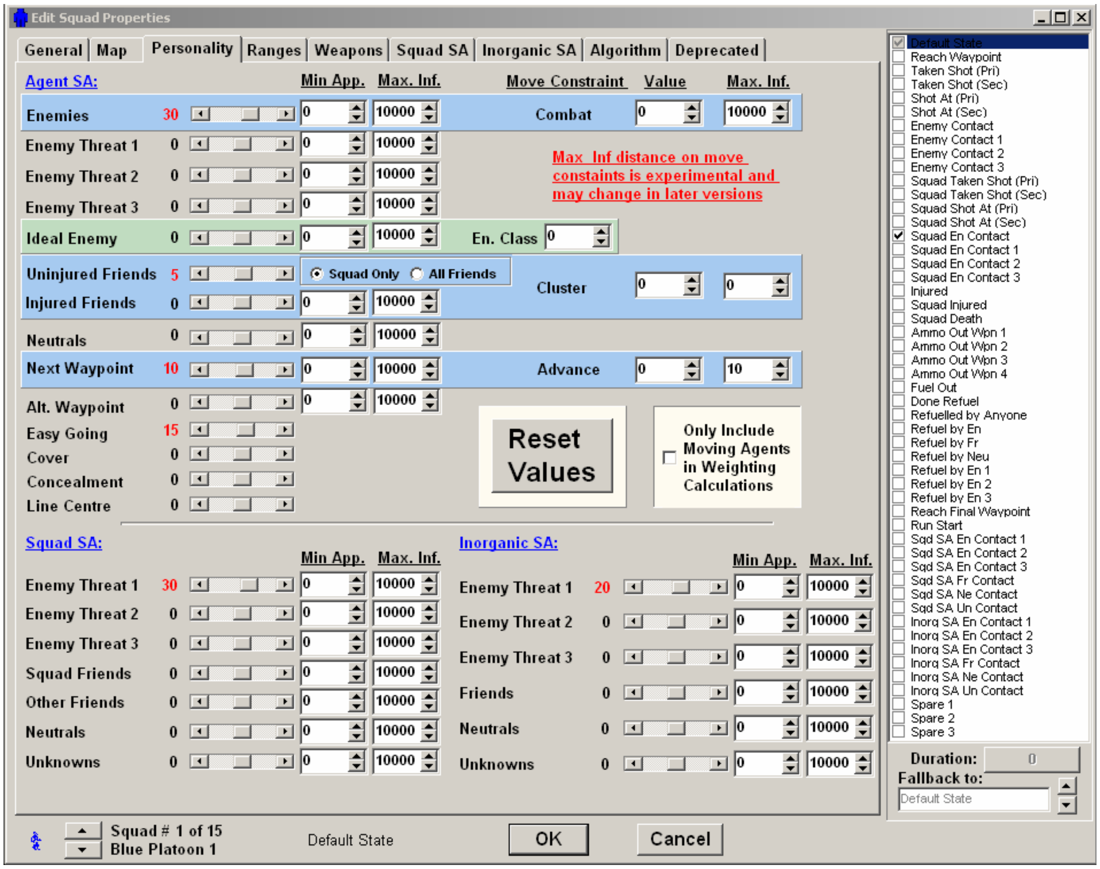


Figure 6. Personality Settings of Squad 1 in Default State.

Checking a trigger state in the *Trigger State* window allows the user to change the personality weightings, or other parameters in other tabs, of the agents based on certain actions of other agents or how an agent is passed information. The trigger state is given a user defined duration and fall-back state once the specified time in the trigger state has elapsed. Both these are shown at the bottom of the *Trigger State* window. For example, the state change in Figure 7 is for the blue patrol. Upon enemy contact, the patrol will have a propensity to seek cover for a duration of 100 time steps, and then return to its default personality. This represents the doctrinal tactic of seeking cover, returning fire, and then proceeding to clear a building.

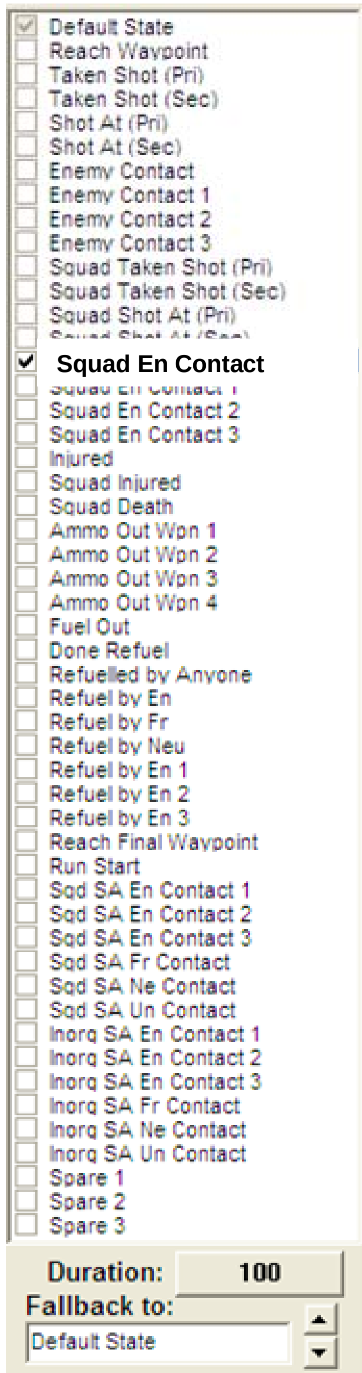


Figure 7. Duration and Fallback for the Squad En Contact Trigger State.

5. Ranges Tab

Figure 8 displays the Ranges Tab for the blue platoon. The characteristics in this tab can change based on the state of the squad. In the *General* window we can designate an icon for the squad, give it an allegiance, assign it a threat for the enemy's SA, give it an agent class so that the enemy can determine what weapon to use against it, and choose the squad's movement speed. Our blue platoon, like other foot-mobile agents, has a movement speed of 1, which means it can move one pixel in one time step.

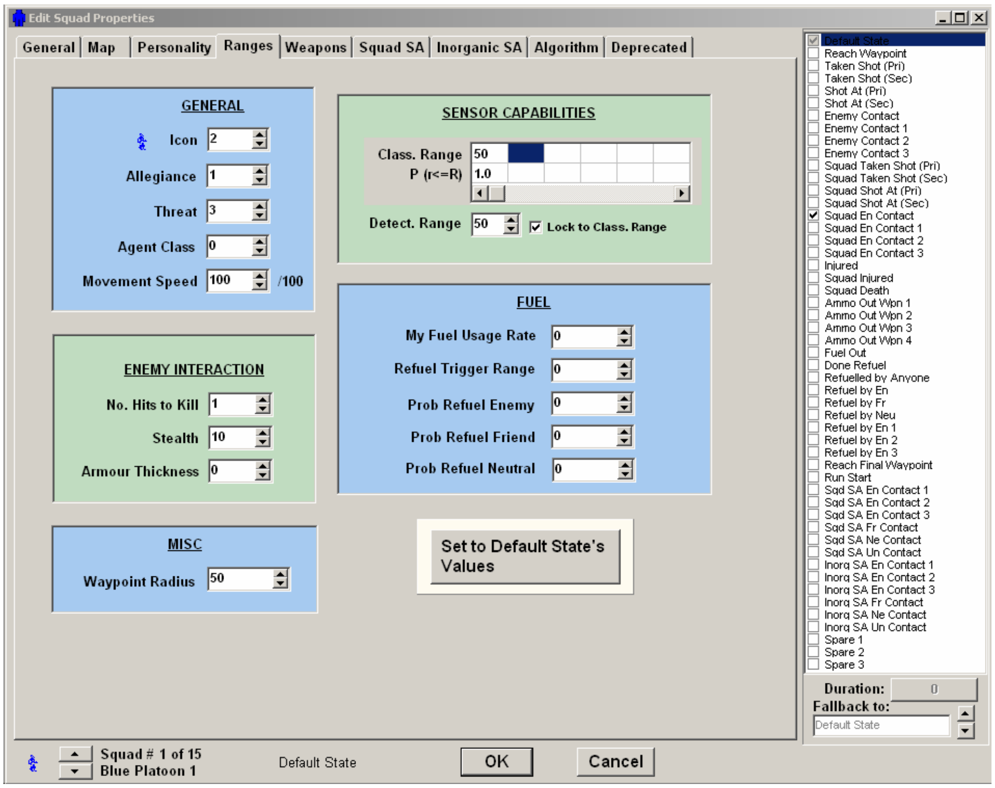


Figure 8. Squad Ranges Tab.

The *Enemy Interaction* window designates how many hits it will take to kill the agent, the agent's stealth, and the armor thickness. The stealth value is the percent of time (0-100) that the agent will not be detectable. For our scenario, the blue's stealth is very low due to its desire to show a presence. The red stealth is much higher but will be reduced if it engages the blue forces.

The *Misc* window designates how close an entity must be to a waypoint in order to consider it reached. A value of 0 means that each entity would have to be exactly on top of the waypoint in order to consider it reached. This would result in the squad being channeled into a particular area, which would decrease dispersion and increase the chances of casualties. For the purpose of our scenario, the agent must be within 50 meters to consider the waypoint reached. The *Sensor Capabilities* window for an agent is used to specify the range over which it can detect and classify another agent. Classification ranges can be further broken down into probabilities at different ranges. For our scenario, we have locked the detection range to the classification range and set the range to 50 for our blue platoon. This distance is in keeping with MCWP 3.35.3. The *Fuel* window is used for agents needing refueling. It was not used in this scenario.

6. Weapons Tab

The Weapons Tab is shown in Figure 9. The Weapons Tab allows the user to define how many weapons the agents can use, as well as the weapon types and accuracies. In this scenario the blue agents have greater kill probabilities than red agents to reflect better weapons and training. The weapon type used by all agents, other than the IED, is a kinetic energy or small arms weapon. Blue agents also have a second weapon type that allows them to engage targets using the inorganic SA provided to them from the UAV. Because our forces will normally be operating under strict ROE in this type of scenario, the weapon used based on inorganic SA is also a small arms direct fire weapon, rather than a high explosive round, such as artillery or grenade launchers. The IED is a high explosive devise with a kill radius. Ranges for all the weapons in this scenario are based on MCWP 3-35.3.

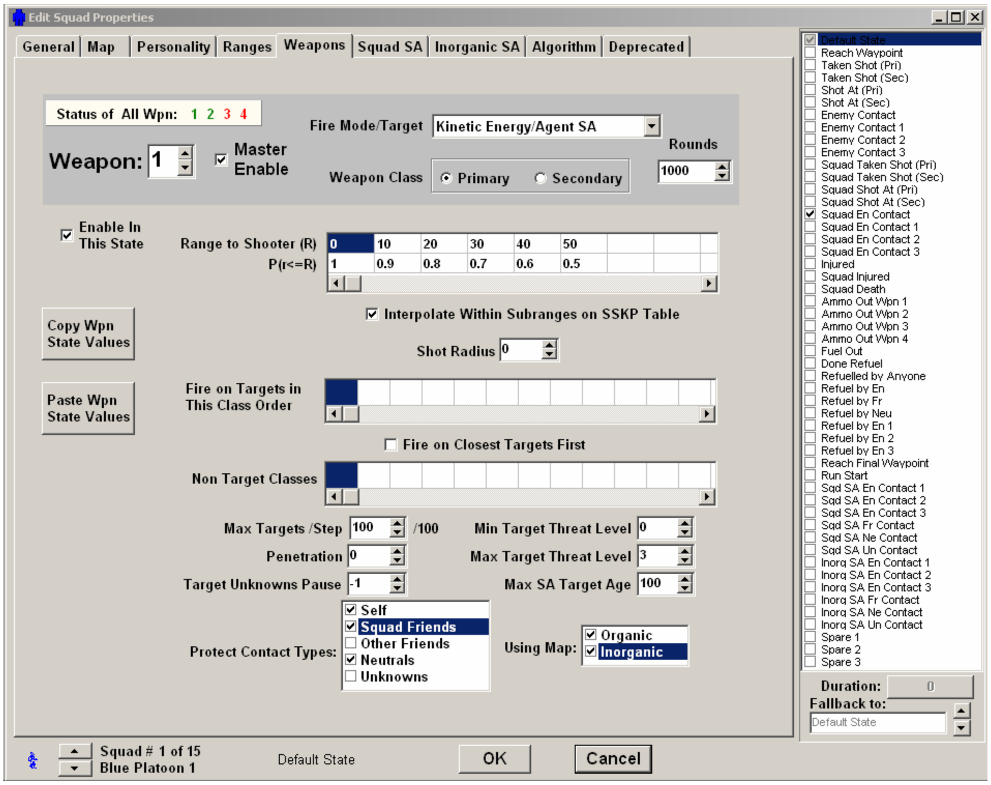


Figure 9. Weapons Tab.

7. Movement

Figure 10 depicts the Algorithm Tab that controls the movements of the agents. The Stephen Algorithm is the default setting and is used for this scenario. This algorithm considers all moves within the range of the agent, and then chooses a move based on the agent's personality weighting and movement constraints. The *Precision Move Selection* determines the randomness in an agent's movement. A low setting corresponds to little randomness, which is the setting for blue agents in our scenario. Red agents have a higher setting, giving them a greater randomness in their movement.

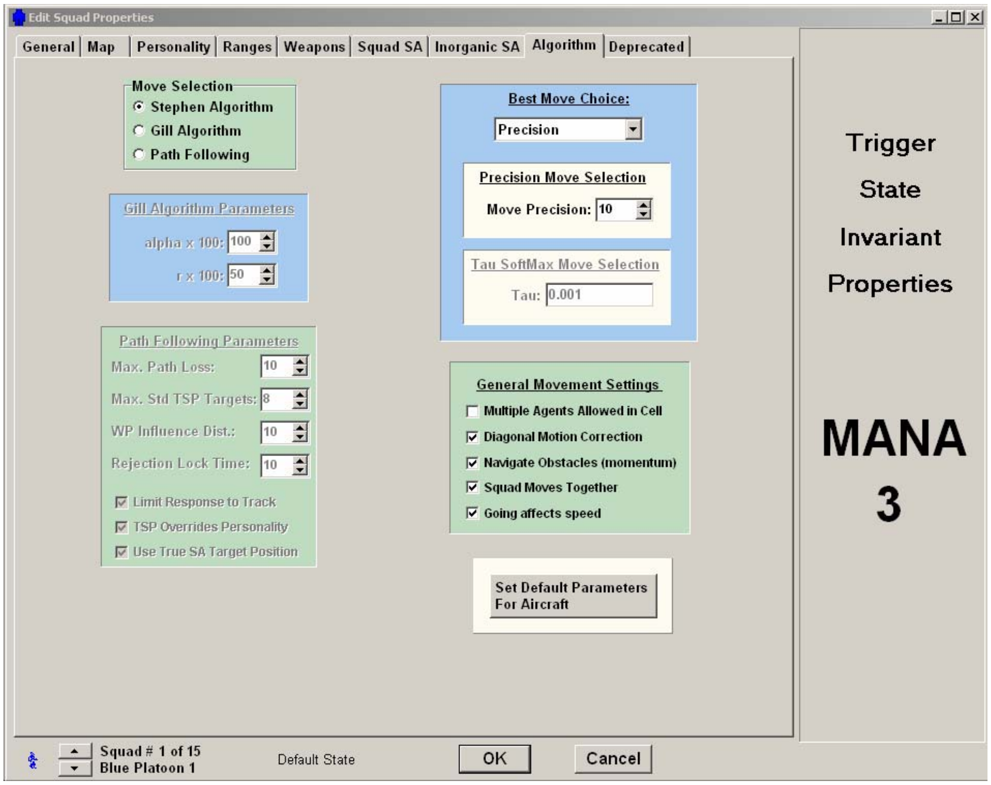


Figure 10. Movement Algorithm Tab.

Under *General Movement Settings* the user can further define movements. For instance, if the *Going affects speed* option is checked, then the type of terrain will affect the agent's speed and ability to navigate obstacles. This option is checked for all agents in our scenario except for the UAV, which flies over structures on the ground.

This concludes our discussion of model development. We have seen that MANA is a simple tool that allows the user to create detailed scenarios in a fairly short amount of time. The model developed was specifically for a small unit conducting patrolling operations in an urban environment with a UAV. From the discussion it is not difficult to imagine countless different scenarios with different parameters that could be examined using this tool.

THIS PAGE INTENTIONALLY LEFT BLANK

III. ANALYSIS METHODOLOGY

The Data Farming environment of MANA is excellent for exploring the effects and interactions of many factors over many levels. MANA coupled with high performance computing provides decision makers with potentially interesting outcomes based on the interactions of the various factors being modeled. With many factors being examined over many levels, it is essential that experimental designs be chosen that can offer an intelligent way to sample over a wide range of factors and levels.

This chapter explains the methodology for analyzing the urban patrol scenario. We will discuss the robust design process that will be used for designing and analyzing our experiment. We will discuss the measures of effectiveness (MOEs) that were chosen for this scenario and the statistical methods for analyzing the data and factors important to the success of the model. Also covered in this chapter is the data collection plan chosen for exploring our MANA scenario.

A. ROBUST DESIGN

The process used to determine the best design for this scenario is known as *robust design*. This approach is an optimization process that espouses that a design's mean performance should not be the only criteria for the best design—a good system design should also be relatively insensitive to uncontrollable factors in the environment. Genichi Taguchi, who used this process in the manufacturing field for engineering product design, pioneered this approach.

> He found that it was often more costly to control causes of manufacturing variation than to make a process insensitive to these variations, and through the use of simple experimental designs and loss functions was often able to greatly improve product performance by 'building in' the quality. [Sanchez et al., 1996]

Although originally used in the manufacturing field, a design insensitive to uncontrollable factors is particularly appealing for military systems. In the combat environment, military systems are constantly affected by uncontrollable sources of variation. The framework for a robust design that follows is detailed in [Sanchez et al., 1996]: (1) select the performance measures; (2) specify a loss function; (3) identify the factors; (4) plan the experiment; (6) analyze the results; (7) refine the metamodels; (8) select the best process design. In the following sections we examine each step.

B. MEASURES OF EFFECTIVENESS (MOE)

An MOE is a quantitative measure of performance. In our scenario we have chosen the red:blue kill ratio, also known as the exchange ratio (ER). Rather than just look at red kills, we would like a performance measure that takes into account blue casualties. Although we expect blue casualty rates to be high in this scenario, we would like to find a combination of factors that would make the ratio as high as possible. For a robust design it is helpful to have an associated target value τ, which represents the ideal exchange ratio. In a perfect world there would be no blue casualties; however, we know that this is virtually impossible in urban warfare. Actual exchange ratios have varied widely in urban warfare. For instance, the exchange ratio for the battle of Hue City during the Vietnam War was 1.6, while the exchange ratio for the attacking Iraqis during the battle for Khorrasmshahr during the Iraq/Iran War was 0.76 [Lamont, 1999]. Because the battle for Hue was seen as a tactical victory we will use the optimistic value of $\tau = 1.5$ as our target.

C. THE LOSS FUNCTION

The next step in the robust design process is to define a loss function that will convert the performance measure into dimensionless units. This function measures the cost associated with the variation of the system relative to τ. If the system was ideal, our MOE would be equal to τ and the variance would be zero. However, this is highly unlikely to occur, so some way of defining and measuring loss is necessary. For our design we will utilize a quadratic loss function. Letting x and $Y(x)$ represent a vector of decision factors and the associated MOE, respectively, and letting Ω be the noise factors, then the quadratic loss function can be written as:

$$l(x) = c[Y(x) - \tau]^2 \tag{1}$$

where the scaling constant c is used to convert losses into monetary units. For our purposes the scaling constant will be one. From equation (1) the expected loss is defined as:

$$E(l(x)) = c[\sigma_x^2 + (\mu_x - \tau)^2] \qquad (2)$$

where σ_x^2 is the variance and μ_x is the mean associated with the vector of decision factors x; see [Sanchez et al. 1996] for details. Because the variability is not constant across different designs, the loss function in equation (2) is a better measure of a 'good' system than just considering the difference between the mean of the MOE and the target value.

Although we are using a quadratic loss function for this study, it is by no means the only loss function appropriate for designing robust systems. We have chosen the quadratic loss functions for several reasons. The first reason is that the values are easily interpreted to real world terms—the square root of the loss, like the standard deviation, is in the original units of the problem. Second, we know from examining our data that we will not encounter values with the means greater than 1.5. This is important because, assuming that high exchange ratios are better, the quadratic loss function would associate large losses with any exchange ratios much higher than our target value. With this potential problem in mind, another possible loss function is the following:

$$l(x) = -\log(Y(x)) = -\log(\text{exchange ratio}) \qquad (3)$$

The expected loss can then be estimated by the average of the –log(exchange ratio) values for all runs and replications at design point *x*. With this loss function we are not penalized for achieving exchange ratios higher than a specified target value—this loss function does not even require the analyst to specify a target value. One disadvantage of using –log(exchange ratio) is that all observed exchange ratios must be non-zero. It is also not as natural a scale for people to use to compare and contrast alternatives. In our analysis we will consider the results of the loss function in equation (1) with a target value of 1.5, show what happens if a slightly different target value is used, and compare with those using the loss function in equation (2) in order to ensure that our results are consistent across both loss functions. Further work could be done involving more general loss functions, or calibrating the loss functions to reflect the decision-maker's assessment of relative risk, but that is beyond the scope of this study.

D. FACTORS AND SETTINGS

The next step in the design process is to identify factors that might contribute to the MOE. The factors are classified as decision factors and noise factors.

Decision factors are controllable in the real-world setting that is being modeled. The noise factors are those factors that are not controllable, or are difficult or costly to control. Because the primary goal of this thesis is focused on the VTUAV, those decision factors associated with the VTUAV will be of primary interest. Based on some exploratory runs in MANA, we chose to use the seven decision factors and three noise factors in Table 2 in the final production runs.

DECISION FACTORS				
Squad Name	**State**	**Factor Name**	**Low Setting**	**High Setting**
VTUAV	Default	Sweep Width	20	250
		Observation Cover	0	20
		Speed	300	1000
		Latency	0	100
		Comm Reliability	5	95
		Information Accuracy	5	95
Blue Platoon	Default	Aggressiveness	-5	30
NOISE FACTORS				
Squad Name	**State**	**Factor Name**	**Low Setting**	**High Setting**
Civilian	Default	Red Influence	10	50
Red	Enemy Contact	Aggressiveness	-5	30
	Default	Stealth	0	90

Table 2. Decision Factors and Noise Factors

In Table 2, the decision factors and noise factors are outlined by squad name, state of the agent, the factor name, and the low and high settings. The sweep width of the VTUAV is related to the field of view. Because the battle field in MANA has been defined as 1 meter equal to 1 pixel, the conversion is straightforward for the sweep width. The settings range from 20 to 250 meters. The observation cover factor is the VTUAV's propensity to provide observation cover to the blue platoon upon enemy contact. Speed in MANA is relative to the slowest entity on the battlefield. In our scenario the red and blue infantry both have a speed of 5 mph. The VTUAV's speed ranges between 13 nautical miles per hour and 44 nautical miles per hour. These speeds are relatively slow, but consistent with urban surveillance. Latency is the delay in communication between the VTUAV and the blue platoon. The settings are based on time steps. For example, a value of 100 translates into a 100 time step delay in information reaching the blue platoon. Communication reliability is the likelihood that a message will be successfully delivered to the receiving squad. Information accuracy is the probability that a contact's type will be passed correctly to the receiving squad. The final factor is blue aggressiveness. This controls the blue platoon's propensity to move toward enemy contacts.

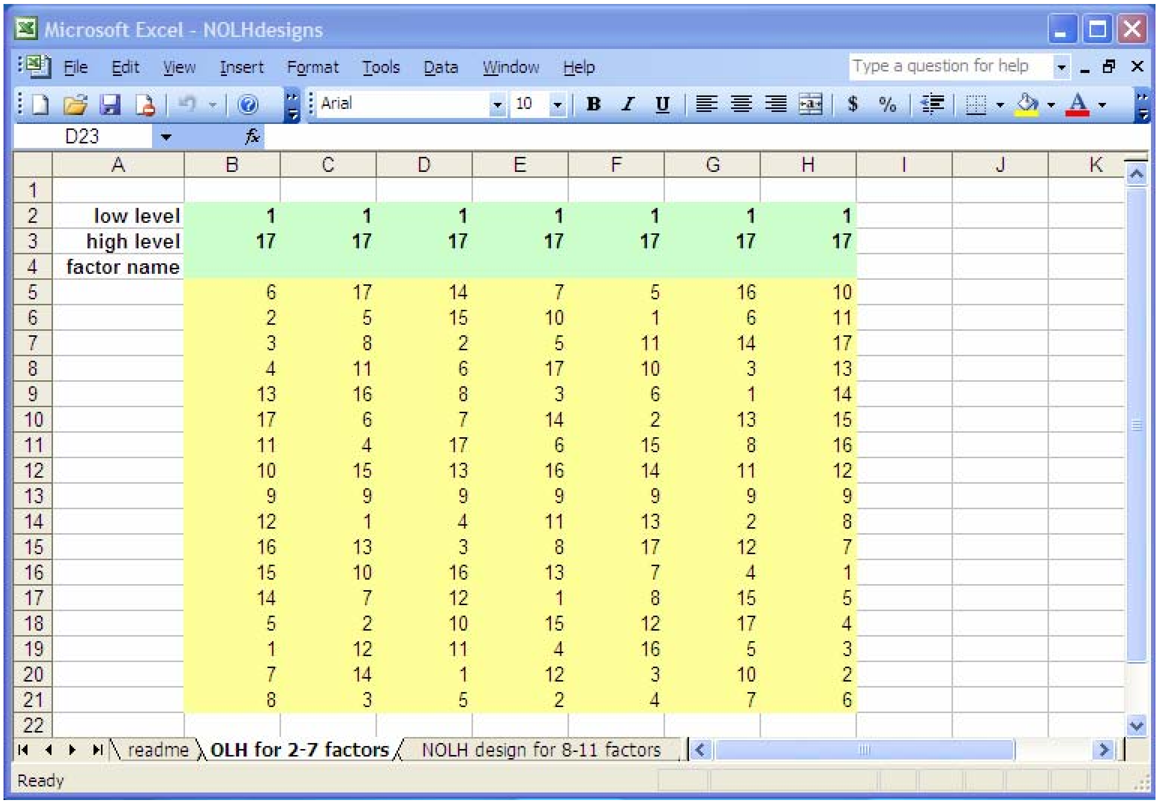
The noise factors chosen are red influence on the civilians, which affects civilian hostility towards blue forces, red aggressiveness, and red stealth. A civilian's hostility is affected by nearby red agents. Upon contact with a red agent, a civilian becomes hostile towards blue forces for a number of time steps, and then reverts back to their neutral state. This noise factor has the potential to be somewhat controllable through various pacification efforts not explored in this study. For the purposes of our investigation we use a range of potential hostility to include civilian hostility as a noise factor. Red aggressiveness and stealth are the final two noise factors for our study.

E. EXPERIMENTAL DESIGN

After choosing the factors and levels we must now focus on the data collection plan. For our study we will use a crossed decision factor × noise factor plan. This approach uses the same plan for each of the noise factors, which allows us to examine the variability across the noise space [Sanchez et al., 1996].

Utilizing a full factorial design for our study would not be practical given the levels we wish to examine and expected non-linear response. For example, if we were to look at our 10 factors each having only 4 levels, we would need 4^{10} design points. This would require 1,048,576 runs to obtain a single piece of data for each design point. If it took only one minute to run the simulation it would require almost 2 years for a single data point per design point. Replicating the design to gather information about the distribution of results for each design point would further increase the time required for data collection. Obviously this approach is not practical for even a modest number of factors with many levels.

Given the factors and levels we wish to examine, we chose a Latin Hypercube Design (LHC). The LHC designs are excellent for space filling and used to efficiently look at many factors with many levels when concerned about extreme non-linearity [Lucas et al., 2002]. This is done by not only sampling on the edges but also in the interior of the design area. For our study we will use a Nearly Orthogonal LHC (NOLHC) design. This design provides us with two important characteristics: orthogonality and good space filling [Cioppa, 2002]. Orthogonality is important in order to have low correlation, reducing the effects of multicollinearity on the model. Good space-filling is important because the design points are scattered throughout the experimental region making it easier to detect any nonlinearities. In order to construct a NOLHC for this study, a Microsoft Excel Spreadsheet (implementing Cioppa's designs) constructed by Professor Susan Sanchez was used to generate the design points [Sanchez, 2004]. Figure 11 displays the spreadsheet for a 1-7 factor design. The user can pick an orthogonal or nearly orthogonal design based on the number of factors to be examined. The minimum and maximum levels and names for each factor are then entered into the appropriate cells. The default factor levels (given as the integers 1-17 in Figure 11) are appropriately converted. Each row then specifies the combination of factor levels for a single design point. The ranges used in our investigation mean that some rounding of the factor levels occurs, so the resulting design is not quite orthogonal.



	A	B	C	D	E	F	G	H
1								
2	**low level**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
3	**high level**	**17**	**17**	**17**	**17**	**17**	**17**	**17**
4	**factor name**							
5		6	17	14	7	5	16	10
6		2	5	15	10	1	6	11
7		3	8	2	5	11	14	17
8		4	11	6	17	10	3	13
9		13	16	8	3	6	1	14
10		17	6	7	14	2	13	15
11		11	4	17	6	15	8	16
12		10	15	13	16	14	11	12
13		9	9	9	9	9	9	9
14		12	1	4	11	13	2	8
15		16	13	3	8	17	12	7
16		15	10	16	13	7	4	1
17		14	7	12	1	8	15	5
18		5	2	10	15	12	17	4
19		1	12	11	4	16	5	3
20		7	14	1	12	3	10	2
21		8	3	5	2	4	7	6
22								

Figure 11. LHC Design Spreadsheet (from: Sanchez, 2004).

In order to better utilize the space filling properties of the LHC design, we linked two 7 factor OLH designs together using an algorithm described by Cioppa [2002, p. 54]. The resulting scatter plot and correlations for each pair of factors are shown in Figures 12 and 13 respectively. Each region is reasonably filled with points, so our experiment will provide insight for intermediate values of the factors, not just the extremes. When linked together, we have an experimental design with 33 configurations. Crossing this design with a similar design for the noise factors gives us 1089 design points (33 x 33). For each of the design points we will conduct 40 replications for a total of 43,560 runs.

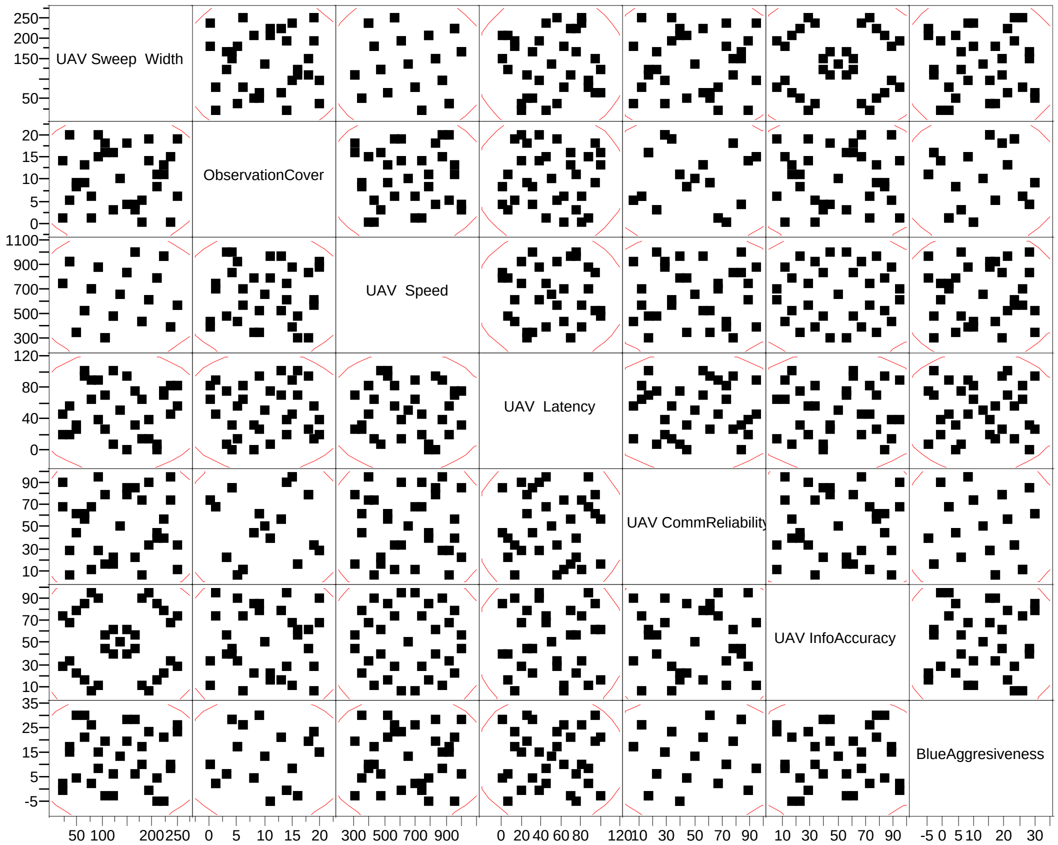


Figure 12. Scatter Plot.

Figure 12 shows that our design has reasonable space-filling behavior. Table 3 shows that despite the rounding necessary to obtain the factor levels for our experiment, all pairwise correlations are still very near zero.

	UAV Sweep Width	Observation Cover	UAV Speed	UAV Latency	UAV Comm Reliability	UAV Info Accuracy	Blue Aggressiveness
Sweep Width	1	-0.0007	-0	-0.0017	0.0019	0	-0.0086
Observation Cover	-0.0007	1	0	-0.0079	0.009	-0.0018	0.0044
UAV Speed	-0.0014	0	1	0.0007	0.0033	0	0.0069
UAV Latency	-0.0017	-0.0079	7E-04	1	0.0031	0.0024	-0.0038
UAV CommReliability	0.0019	0.009	0.003	0.0031	1	-0.0013	-0.0045
UAV InfoAccuracy	0	-0.0018	0	0.0024	-0.0013	1	0.0059
BlueAggresiveness	-0.0086	0.0044	0.007	-0.0038	-0.0045	0.0059	1

Table 3. Correlation Matrix

F. CONDUCT THE EXPERIMENT

With the scenario complete and design points determined, the factors are now ready to be farmed. The MITRE Corporation, in support of the Marine Corps' Project Albert, maintains a supercomputing cluster that supports data farming projects. After emailing the MITRE support team an XML file containing the base scenario, a separate design file listing the factors to be examined and the corresponding factor settings for each design point, and the number of replications, a script file is created that varies the factor levels according to the user-specified design. Output files are returned in comma separated value (.csv) format [Hakola, 2004].

After running 40 replications of the experiment for each design point, we collect the mean and variance for each point. Letting Y be the random function of the decision factors $\{X_i\}$ and the noise factors $\{W_i\}$, we have the following equations for the mean response Y_i and mean variance V_i corresponding to the decision factor configuration i and noise configuration j:

$$\overline{Y}_{i\cdot} = \frac{1}{n_w}\sum_{j=1}^{n_w}\overline{Y}_{ij} \tag{4}$$

$$\overline{V}_{i\cdot} = \frac{1}{n_w-1}\sum_{j=1}^{n_w}(\overline{Y}_{ij}-\overline{Y}_{i\cdot})^2 + \frac{1}{n_w}\sum_{j=1}^{n_w}s_{ij}^2 \tag{5}$$

where n_w is the number of noise factor points [Sanchez et al., 1996]. The total variance of the design point in equation (2) is the sum of the inherent variance of the simulation run and the extrinsic variance across the noise space.

G. ANALYZE THE RESULTS

After running the model and collecting the mean and variance for each design point, we use regression to develop metamodels for the mean and logarithm of the variance. Regression analysis is used to take advantage of the relationship between two or more variables so that we can gain information about one of the variables by knowing the values of the others [Devore, 2000]. Our metamodels are functions of the decision factors taken over the noise space. We use a design for fitting main effects, interactions, and quadratic effects. The variance is transformed logarithmically for stability, and the initial models will be of the form [Sanchez et al., 1996]:

$$\mu \approx \hat{\bar{Y}}_i = \hat{\beta}_o + \hat{\beta}_1 X_1 + \cdots + \hat{\beta}_k X_k + \hat{\beta}_{1,2} X_1 X_2 + \cdots + \hat{\beta}_{k-1,k} X_{k-1} X_k + quadratic \qquad (6)$$

$$\ln(\sigma^2) \approx \ln(\hat{\bar{V}}) = \hat{\gamma}_o + \hat{\gamma}_1 X_1 + \cdots + \hat{\gamma}_k X_k + \hat{\gamma}_{1,2} X_1 X_2 + \cdots + \hat{\gamma}_{k-1,k} X_{k-1} X_k + quadratic \qquad (7)$$

The data analysis software package used for this thesis was JMP Statistical Discovery Software™.

H. REFINE THE METAMODELS

The initial models will be evaluated based on their coefficient of determination (R^2) value. This value is the proportion of variability in the response that is explained by the model. Clearly, R^2 alone may not be the best measure of a 'good' model. With a full model of main effects, interactions, and second order polynomials it is possible to have an extremely high R^2 but few degrees of freedom for error. It would also be difficult to explain what is going on with a model of this many terms, rendering it virtually useless. The initial model should be assessed and any insignificant terms removed. The test used to determine which individual terms will remain in the model is the t-test. The equation for the t-statistic is the following [Hamilton, 1992]:

$$t = \frac{b_k - \beta_k}{SE_{b_k}} \qquad (8)$$

where b_k is the coefficient estimate for factor k, β_k is the hypothesized value of the coefficient for factor k, and SE_{b_k} is the standard error of b_k. The associated *p*-value of the t-statistic will determine the significance of the term. Reasonable levels of significance are usually defined as any *p*-value less than 0.05 or 0.01. For our study we will use a value of 0.05.

I. SELECT THE 'BEST' DESIGN

We can use the loss function to examine the metamodels to determine the most desirable decision factor values for our scenario. These values may be different than those we would suggest if we were basing our decision on mean performance alone.

This chapter has outlined the robust design methodology and techniques for analyzing the data of our scenario. Chapter IV will present a detailed analysis based on this methodology.

THIS PAGE INTENTIONALLY LEFT BLANK

IV. DATA ANALYSIS

This chapter details the analysis and findings. We proceed using the methodology described in the previous chapter. We will begin by examining the data and giving an initial assessment with graphical analysis and regression trees. We will then analyze the data using multiple regression models with main, interaction, and quadratic terms. Next, we will refine the models by including only the relevant terms. Using the refined models with the loss equation detailed in Chapter III, we will select the best design.

A. INITIAL ASSESSMENT

Upon receipt of the data, we examined the data to make certain there were no problems with the data quality. We consolidated the runs of each of the 1089 design points and produced our mean exchange ratios. The distribution plot of the data is shown in Figure 13.

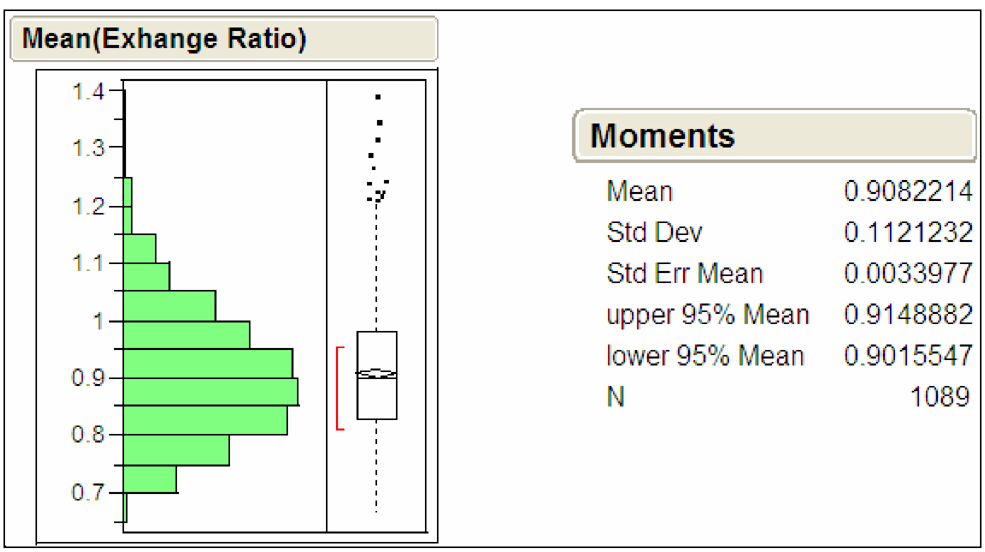


Figure 13. Distribution Plot of Mean(Exchange Ratio).

We see from the distribution plot, as expected, all the exchange ratios are positive. Also as mentioned in Chapter III, all mean exchange ratios are less than our target value of 1.5, so using a target value of 1.5 provides a motivation toward continual improvement. The distribution has positive skewness, including some high values that would be considered outliers if the data followed a normal distribution. These outliers correspond to good outcomes, but keep in mind that in a robust design framework the best decision might not produce the same outcome as a decision based on mean performance alone.

After examining the data we then developed a regression tree, which can give insights to the possible important decision factors and noise factors that drive our model. A regression tree partitions the data recursively according to the relationship between the decision factors and the response [*JMP® Statistics and Graphics Guide*, 2002], but does not assume a specific structure for the form of this relationship. Because the focus of this study is developing a robust model, we will begin by developing a regression tree using only the decision factors. Later in the chapter, we will build a regression tree using both the decision and noise factors to see if we can gain additional insights into the development of the appropriate tactics in various settings. Figure 14 is a regression tree considering only the decision factors.

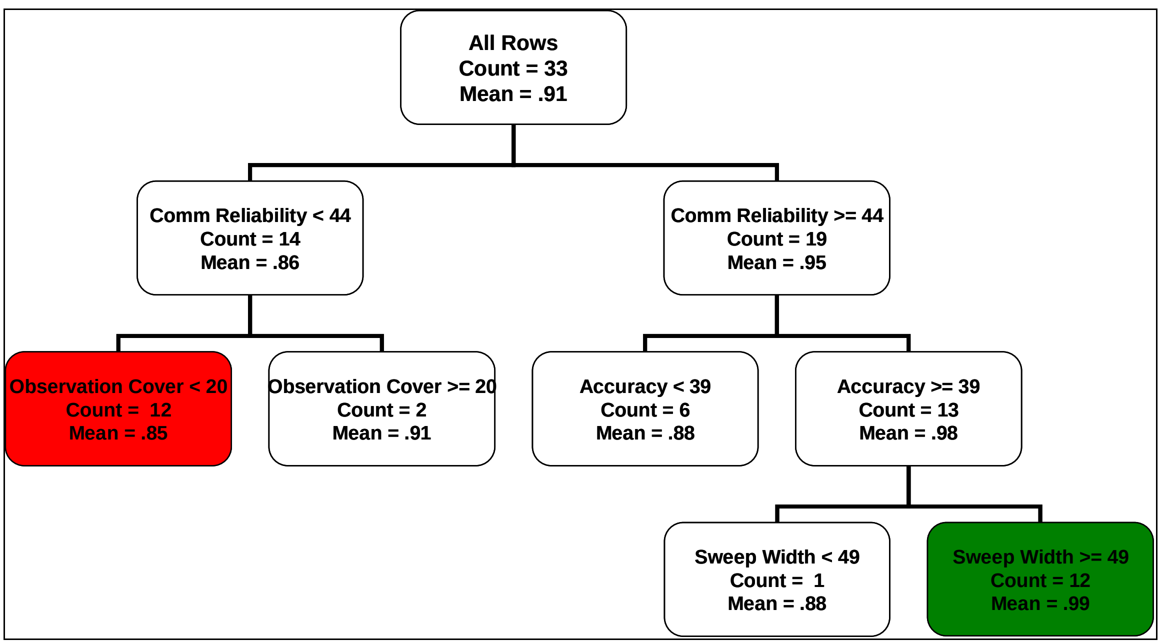


Figure 14. Regression Tree, Decision Factors Only.

With 33 design points represented and the total mean shown in the top box, we have an R^2 of .89 after only 4 splits of the data. The box at the bottom left of the tree (colored red) represents the least favorable conditions, yielding an average exchange ratio of 0.85. The box at the bottom right of the tree (colored green) represents more favorable conditions, yielding an average exchange ratio of 0.99. (In this instance we show only one red and one green leaf, but in general there could be several leaves with similar values.) For instance, and not surprisingly, the best exchange ratios are achieved with high communication reliability, high accuracy, and a high sweep width. It is interesting to note that if the sweep width is low a higher accuracy does not improve the mean.

With these initial insights into the data we will now begin to develop our regression models for a more detailed look at our decision factors.

B. DEVELOPMENT OF THE MODELS

As outlined in the previous chapter, we use regression to develop metamodels for the mean exchange ratio and the logarithm of the variance as functions of the decision factors.

1. Mean Exchange Ratio Main Effects

The regression model that we are developing associates the average response (calculated over the noise space) to the decision factors. We began by using only main effects to get an idea of the impact of these factors alone on our model. We developed the main-effects model using the mixed stepwise function in JMP. This function uses alternating forward and backward steps, allowing terms to enter the model on the forward step and leave the model on the backward step, based on a significance level for each. For our model we allowed terms to enter the model at a significance of .25 and removed terms with significance less than .05.

The main-effects model that resulted consisted of three terms with an $R^2 = .78$, indicating that 78% of the variability in the exchange ratio is explained by these three terms (p-value < .0001). Reliability, accuracy, and aggressiveness were found to be significant at the .05 level and the plot of the residuals vs. the predicted values is shown in Figure 15. The solid red line corresponds to predictions from the regression equation, while the dashed red lines represent a 95% confidence band for the mean predicted values. Ideally, the points should be scattered around the prediction line with no apparent pattern. We see from the graph that there is a group of points that fall below the lower confidence limit. While the R^2 and the graph look reasonably good, those points indicate that we might be able to do better.

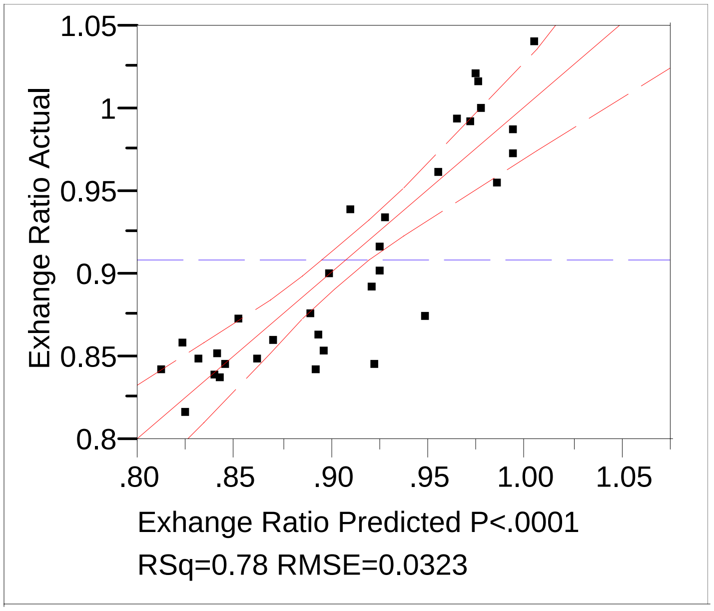


Figure 15. Actual vs. Predicted Exchange Ratio.

2. Final Model Mean Exchange Ratio

Again using the stepwise function in JMP with the same significance criteria in the main effects model, we developed the final model. The final model consisted of six terms: four main effects, one interaction, and one quadratic with an overall p-value < .0001. Looking at the actual versus predicted exchange ratio in Figure 16 we see that the group of troublesome points in Figure 15 has decreased. There does not appear to be any pattern in this plot, indicating the assumption of independent and identically distributed errors is reasonable. The R^2 for this model is .91, giving us better predictability than just the main-effects model while still having relatively few terms. The final model of the exchange ratio is represented by the following equation:

$$\begin{aligned}&ExhangeRatio \approx 0.7598 + 0.00007(Sweep\_Width) + 0.00157(Reliability)\\&+0.00122(Accuracy) + 0.00149(Blue\_Aggressiveness)\\&+0.000022[(Reliability - 50.0606) * (Accuracy - 50.0606)]\\&-0.000004[(Sweep\_Width - 135.061) * (Sweep\_Width - 135.061)]\end{aligned} \quad (8)$$

The interaction and quadratic term have the mean point subtracted from the factor value to ensure proper scaling.

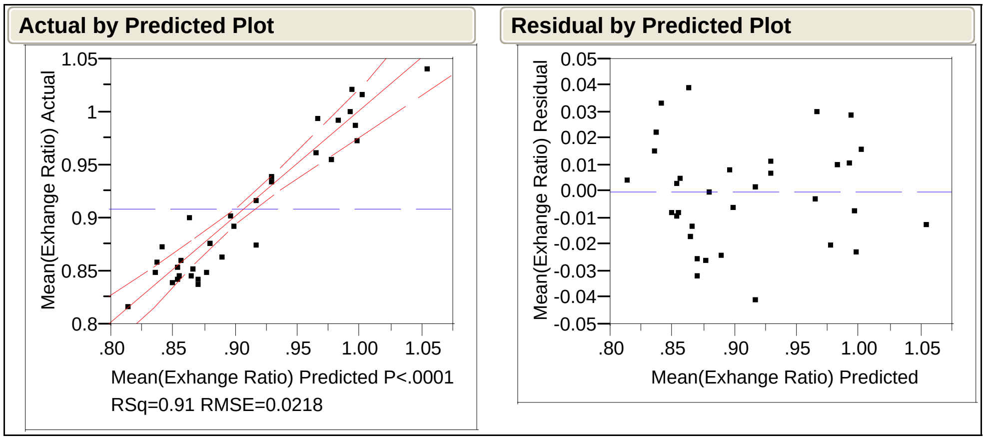


Figure 16. Actual and Residual vs. Predicted Exchange Ratio.

Summary statistics for the final model can be seen in the Appendix. Of the seven decision factors, four appear as main effects in the final model. Although sweep width has a p-value of .19 it has been included as a main effect due its significance (p-value < .0002) as a quadratic term in the model. Figure 17 displays the leverage plots for the significant main effects of the model. The UAV communications reliability has the strongest influence, followed by UAV information accuracy and blue aggressiveness, respectively.

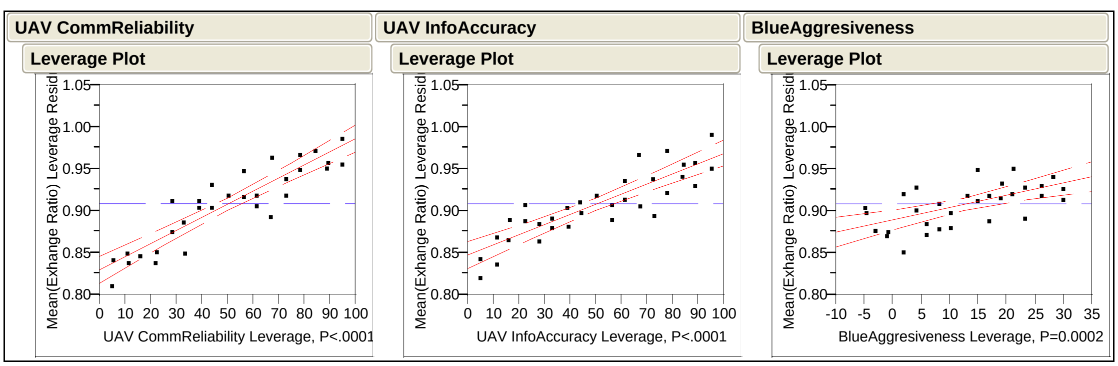


Figure 17. Leverage Plots.

The model's interaction term, communication reliability and information accuracy, can be seen nicely using the contour plot in Figure 18. The blue regions circled in the upper right-hand corner represent areas with higher mean exchange ratios. Intuitively it seems reasonable that these two factors would have an interaction effect. Perfect communication with imperfect information or vice versa is virtually useless, but—like the regression tree—the contour plot can give us insights into the potential trade space between these two factors. This can be especially important in an urban environment where potential threats can be difficult to identify and communication sporadic.

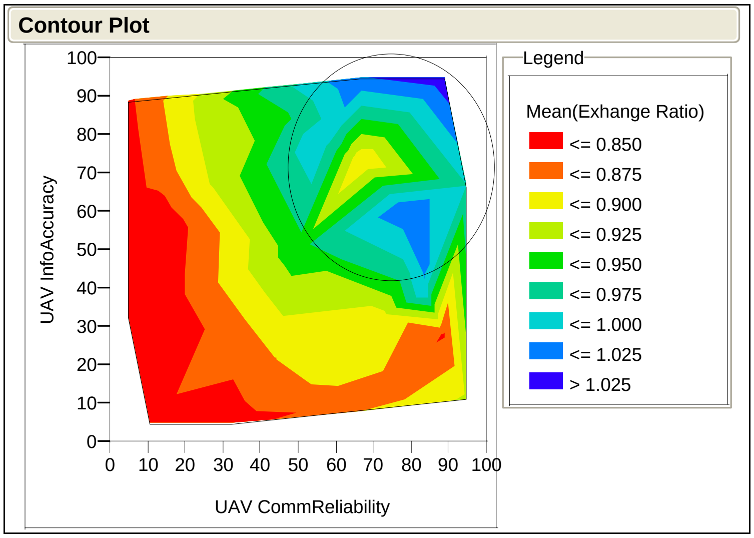


Figure 18. Contour Plot of Accuracy and Reliability vs. Mean Exchange Ratio.

The contour plot in Figure 19 shows the mean exchange ratio as a function of blue aggressiveness vs. information accuracy. As the circled area on this plot shows, we see that as the information we receive becomes more accurate the need for higher aggressiveness in order to maintain high exchange ratios decreases. This could have potential benefits in areas where we want to minimize our aggressive posture in order to win the hearts and minds of the local population.

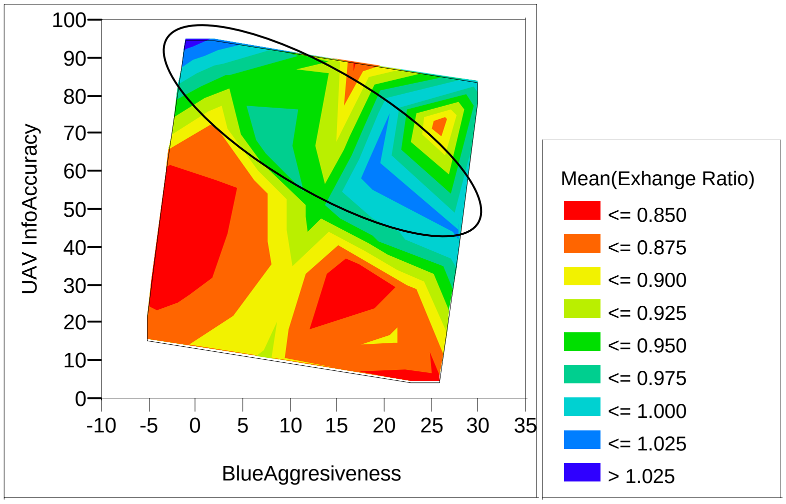


Figure 19. Contour Plot of Accuracy and Aggressiveness vs. Mean Exchange Ratio.

The final term in the model is the quadratic term of sweep width. This term implies that there is a point where too large of a field of view is detrimental to the exchange ratio. Generally this would seem counterintuitive; the wider area a UAV can see the better. However, if we look at this factor in the context of the situation we are modeling it seems to make more sense. The area of the patrol is relatively small and the capability of a small foot mobile unit to cover large distances in an urban environment is limited. With the UAV able to detect more red agents at greater distances, the blue forces will move to engage these detections. If the detections are lost by the UAV before the blue forces arrive, the blue forces will move back to their original patrol route or to the most current UAV detection. Moving over larger distances it is not difficult to imagine an accordion effect between more recent detections, resulting in fewer engagements and lower exchange ratios. It might be argued that this is an artificiality of the model, but it could also be seen as information overload. With too much information the blue force becomes indecisive and ineffective. Figure 20 displays the prediction profiler graph from JMP. The profiler is a useful tool to see how the predicted values change as you change one factor at a time. Figure shows the settings that maximize the mean exchange ratio based on the metamodel. Notice the curve for sweep width and the point of decreasing effectiveness. This means that moderate sweep values are best.

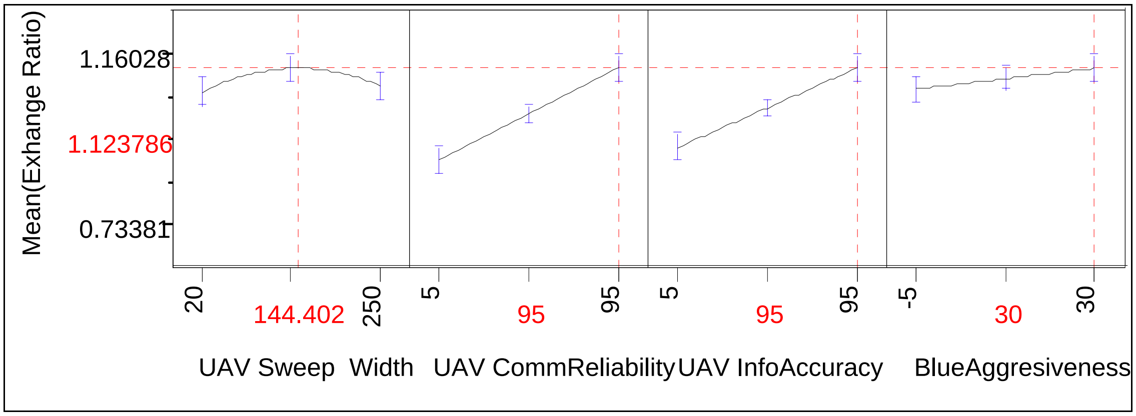


Figure 20. Prediction Profiler with Optimal Settings for Maximum Exchange Ratio.

3. ln(Variance) Model

The ln(Variance) model was developed in the same manner as the mean exchange ratio model. We considered all main effects, two-way interactions, and quadratic effects, allowing terms to enter the model with significance greater than 0.25 but eventually eliminating terms with significance less than .05. Using the stepwise function in JMP we obtain the following metamodel equation:

$$\begin{aligned}
&\ln(\sigma^2) \approx -2.500952 + 0.00060(Sweep_Width) + 0.00671(Reliability) \\
&+0.00532(Accuracy) + 0.00619(Blue_Aggressiveness) \\
&+0.00003[(Sweep_Width - 135.061)*(Accuracy - 50.0606)] \\
&-0.00002[(SweepWidth - 135.061)*(Sweep_Width - 135.061)] \\
&-0.00013[(Reliability - 50.0606)*(Reliability - 50.0606)]
\end{aligned} \tag{9}$$

Summary statistics for the final model of ln(variance) can be seen in the Appendix. Figure 21 displays the graphs for actual and residual by predicted. We see from the graph that the model produces an R^2 of .85. The regression is statistically significant (p-value < .0001).

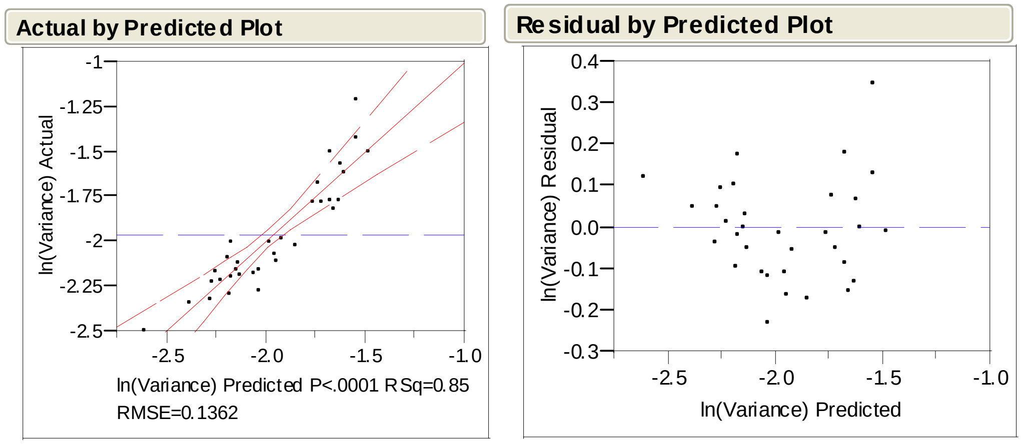


Figure 21. Actual and Residual vs. ln(Variance) Predicted.

In order to make use of the maximization function in the profiler we maximized the quantity [-ln(variance)] in order to get the best settings for minimum variance as seen in Figure 23.

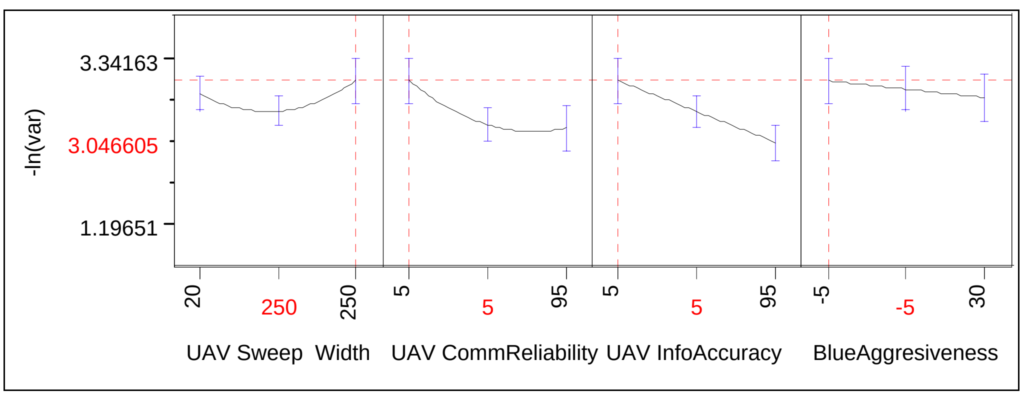


Figure 22. Prediction Profiler with Optimal Settings for Minimum Variance.

Looking at the optimal settings for minimum variance, the values are almost all at the other end of the spectrum from the optimal settings for the maximum exchange ratio. With the settings for reliability and accuracy at 5 the UAV is virtually nonexistent as an intelligence gathering asset. The aggressiveness setting at -5 translates into a blue force avoiding engagements with the red forces. Essentially, in order to keep the variance at a minimum, the blue force should avoid fighting. Of course this is not an option in urban combat.

In an ideal world we would be able to simultaneously maximize the exchange ratio and minimize the variance using the same decision factor settings. Unfortunately this is rarely the case. As the profiler plots and Figure 23 demonstrate, for our scenario it is impossible. Figure 23 displays the mean exchange ratio vs. the variance. We see that as the mean exchange ratio increases so (in general) does the variance. Even though there does appear to be a general trend, this is not a direct relationship. There are differences in the variance especially at high exchange ratios. This is not surprising given that in order to increase the number of red kills, the blue forces will have to engage.

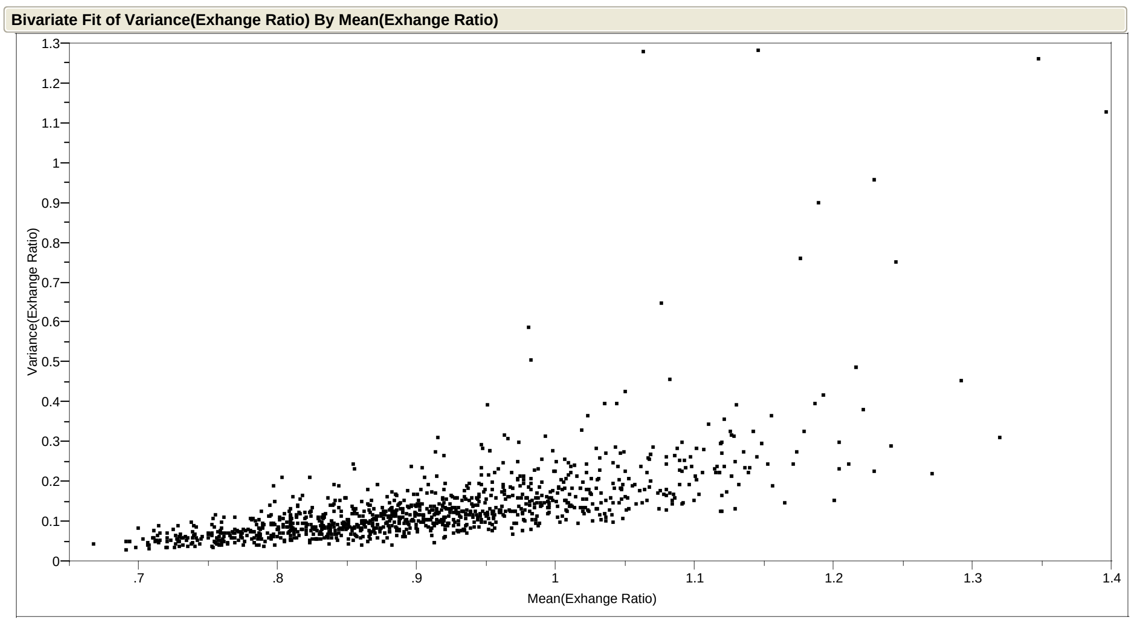


Figure 23. Variance vs. Mean (Exchange Ratio).

We have seen from the profiler that the best mean exchange ratio the model will achieve is 1.16; therefore, if we are to have a chance to come close to our target value of 1.5 we will need increased variability in the loss function. (Note that the increased variability also means the exchange ratio may be much lower.) Now that we have developed the metamodels for the mean exchange ratio and the variance of the exchange ratio, we will now use equations (8) and (9) in order to minimize the loss with respect to our target value of 1.5.

C. CHOOSING THE 'BEST' DESIGN

Using equations (8) and (9), along with the quadratic loss equation (2), we can look for the most robust configuration. Because the data collection plan uses a LHC design rather than a full factorial we will use a grid search over the model's decision factors for the minimum loss.

1. Minimizing the Loss Function

In order to look at all possible combinations of all levels of the four decision factors common to both metamodels would require 65,205,000 combinations. Instead of looking at each level we aggregate the intervals to a more manageable amount of combinations. Using the factors and levels of Table 4, we are able to look at a grid of 9,600 combinations.

Sweep _Width	Accuracy	Reliability	Aggressiveness
20	5	5	-5
40	15	15	0
60	25	25	5
80	35	35	10
100	45	45	15
120	55	55	20
140	65	65	25
160	75	75	30
180	85	85	
200	95	95	
220			
240			

Table 4. Loss Factors and Levels

Table 5 contains the 33 design points with the resulting mean, ln(variance) and loss for our target value of 1.5. The design point with the lowest loss tested is the 7^{th} row (boldfaced and highlighted in yellow) with a loss of 0.433. The design point in row 3 yields the lowest (worst) mean exchange ratio, but the best (lowest) ln(variance); its loss is 0.547—26% higher than the most robust design point. The losses associated with the design points corresponding to the best mean exchange ratio (1.09) and the worst ln(variance) (-1.20) are .436 and .534, respectively.

Sweep Width	Cover	Speed	Latency	Reliability	Accuracy	Aggressiveness	Mean	ln(variance)	min loss tau = 1.5
20	1	738	44	67	73	2	0.88	-2.17	0.504
20	14	738	19	89	28	-1	0.85	-2.19	0.538
34	5	913	56	5	33	17	**0.82**	**-2.48**	0.547
34	20	913	19	28	67	15	0.90	-2.08	0.481
49	8	344	31	44	22	4	0.87	-2.18	0.504
49	9	344	25	61	78	30	0.96	-1.77	0.465
63	**9**	**519**	**94**	**61**	**84**	**30**	**0.99**	**-1.76**	**0.433**
63	13	519	100	56	16	21	0.88	-1.97	0.525
78	1	694	88	67	95	2	1.02	-1.49	0.452
78	6	694	63	11	5	26	0.84	-2.33	0.526
92	15	869	88	95	11	8	0.90	-2.06	0.482
92	20	869	38	28	89	15	0.92	-2.01	0.472
106	16	300	69	16	56	-3	0.84	-2.21	0.543
106	18	300	25	78	44	19	0.96	-1.76	0.460
121	3	475	6	22	39	6	0.85	-2.10	0.540
121	16	475	100	16	61	-3	0.85	-2.00	0.561
135	10	650	50	50	50	13	0.94	-1.66	0.504
149	4	825	0	84	39	28	0.99	-1.56	0.467
149	18	825	94	78	61	19	1.02	**-1.20**	0.534
164	3	1000	75	22	56	6	0.85	-2.15	0.537
164	4	1000	31	84	44	28	1.00	-1.60	0.449
178	0	431	63	73	11	10	0.87	-2.10	0.525
178	5	431	13	5	89	17	0.84	-2.26	0.534
193	14	606	38	89	95	-1	**1.04**	-1.49	0.436
193	19	606	13	33	5	23	0.84	-2.28	0.540
207	8	781	0	44	84	4	0.94	-1.81	0.483
207	11	781	6	39	16	-5	0.86	-2.22	0.519
221	11	956	75	39	22	-5	0.85	-2.31	0.521
221	13	956	69	56	78	21	1.00	-1.41	0.497
236	0	388	81	73	33	10	0.89	-2.00	0.503
236	15	388	44	95	67	8	0.97	-1.77	0.446
250	6	563	81	11	73	26	0.86	-2.15	0.531
250	19	563	56	33	28	23	0.86	-2.16	0.523

Table 5. Mean, ln(variance), and Loss(1.5) for the 33 Design Points

Using equation (2) we determined the factor settings associated with minimum loss for the target value of 1.5 was a combination that had not been tested: Sweep Width = 20, Accuracy = 95, Reliability = 95, and Aggressiveness = 30. The loss associated with these settings was .343 which was 21% less than the best of the design points tested. A validation experiment was run at this setting to see whether or not the final metamodels are still providing a good fit for these factor settings. The validation experiment yielded a mean exchange ratio of 1.06, which is within the 95% prediction interval of (1.007, 1.123). Similarly the variance and loss for the validation experiment, which were .149 and .339 respectively, fell within the 95% prediction intervals computed from the metamodels. This is strong evidence that the model developed from only 33 design points is providing good results in other parts of the design space. This is even more impressive if we consider that the smallest full factorial design that could have looked for main, quadratic and interaction effects would have needed 2187 design points for the decision factors. A full factorial with 33 levels for each decision factor would require over 42.6 billion design points.

2. Insights into the 'Best' Design

With the best design for our model chosen, we then decided to examine the loss function over a large range of possible targets. As mentioned earlier, exchange ratios have varied a great deal in recent history. We decided to look at target values ranging from 1 to 2 with increments of .01 for a total of 101 different target values. Taking the minimum loss value for each target yielded the twelve different designs (or factor setting combinations) shown in Table 6.

Factor Setting	Sweep _Width	Accuracy	Reliability	Aggressiveness
1	240	5	5	30
2	20	95	95	-5
3	20	95	95	0
4	20	95	95	5
5	20	95	95	10
6	20	95	95	15
7	20	95	95	20
8	20	95	95	25
9	20	95	95	30
10	40	95	95	30
11	60	95	95	30
12	80	95	95	30

Table 6. Factor Settings for Minimum Loss for Target Values 1 Through 2

Figure 24 shows the best factor settings for a particular target. Notice that for a target value anywhere from 1.37 to 1.67, factor setting 9 produces the minimum loss. For targets less than 1.1 we see the factor settings approach those that produce minimum variance. Although not shown in the Figure, a target loss of .8 results in factor settings that are equal to those that produce minimum variance. Conversely, as target values rise above 1.1, factor settings approach those that maximize the mean.

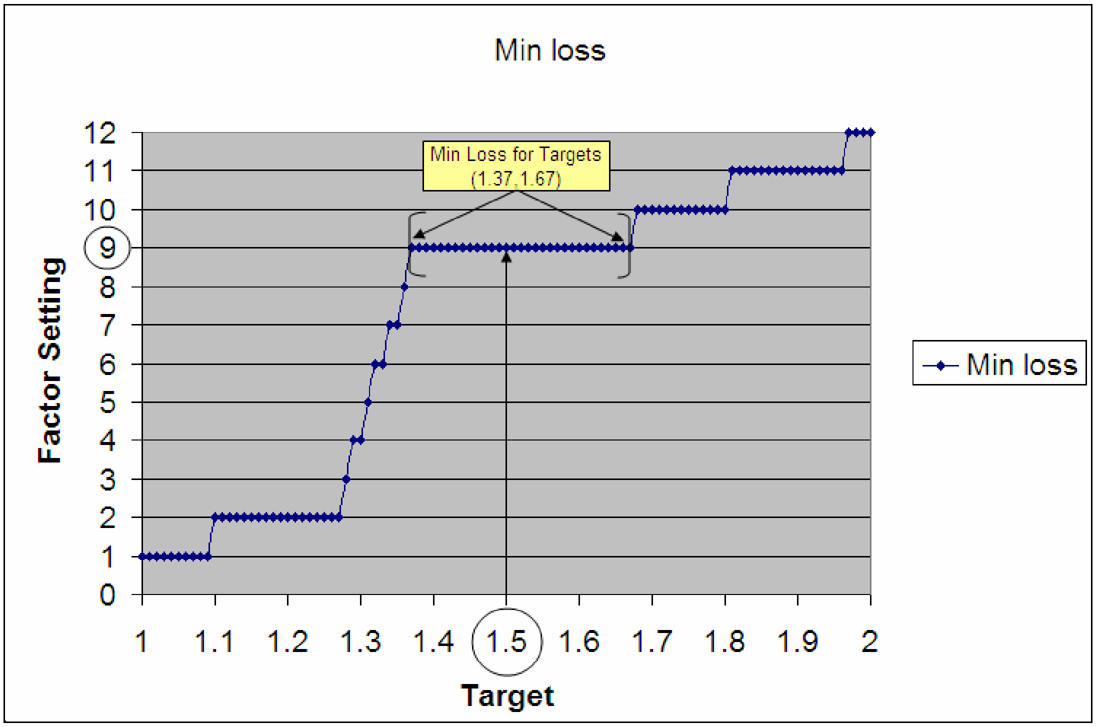


Figure 24. 'Best' Factor Settings for Particular Targets.

As target values rise above the mean of the data, the loss function favors settings that maximize the mean and variance. In order to reach the target value we not only must try to maximize the exchange ratio, but we must also increase the variability so that we have the potential of reaching the target. As stated earlier, in a perfect world we want the exchange ratio to be as high as possible, but in order to achieve that goal we must be willing to accept a large amount of risk.

Recall from Chapter III that in an ideal situation our target value would be equal to the mean and our variance would be zero. Figure 25 represents that situation in as much as the current model can produce it. With our target value at .78 and our variance minimized, we see the lowest loss that our model can produce. The settings for this target value are: Sweep Width = 240, Accuracy = 5, Reliability = 5 and Aggressiveness = -5. These settings are the equivalent to not fighting—which is obviously not a choice in our scenario. The target value would not even be worthwhile to consider, but the graph does give visual insights about the effect of the target value chosen and the importance of variance on the loss function.

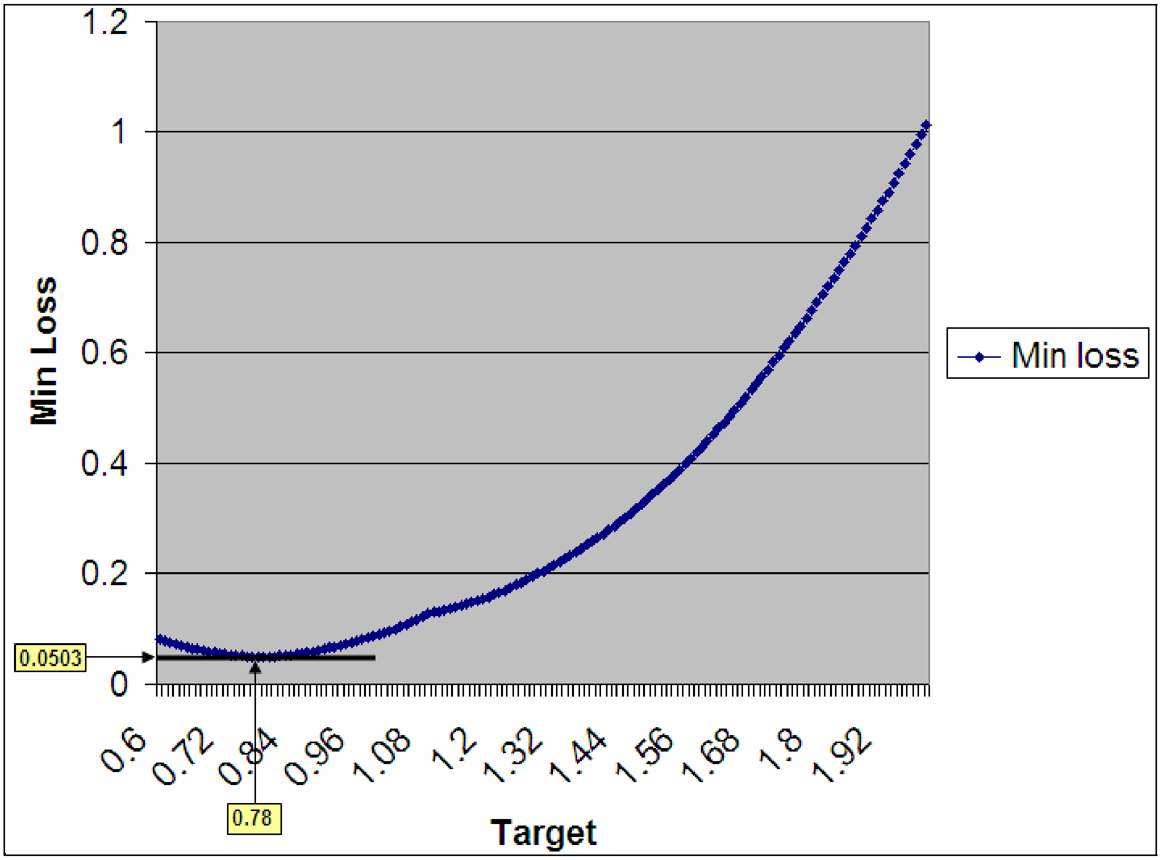


Figure 25. Minimum Loss vs. Target Value.

Let us examine the factors in Table 4 a little closer. Notice that for targets between 1 and 1.1, the UAV is essentially turned off and the blue forces are very aggressive. At values below the target of 1, blue forces eventually become the least aggressive. While these settings might produce the lowest loss of the entire model, it is akin to the adage of "nothing ventured, nothing gained." In turn, if we look at factor settings 2 through 9, we see that the only decision factor that is changing is the aggressiveness of the blue forces. In other words, the only change in factor settings that is required to minimize the loss for target values 1.1 through 1.68 is the blue force's aggressiveness. Once the aggressiveness setting reaches its maximum of 30, the sweep width slowly increases to a maximum of 80 for the target value of 2.

D. AN ALTERNATE LOSS FUNCTION

Now let us consider the alternate loss function of equation (3) that was discussed in Chapter III. By calculating the loss based on $-\log(\text{exchange ratio})$ and plotting this against the loss of the quadratic function of equation (2) we can determine how closely the two sets of results correspond to each other. Figure 26 shows a scatter plot. With an R^2 of 0.74 and a correlation of 0.93 the alternate loss function is in close agreement with the quadratic loss using a target of 1.5. Two design points might be considered outliers, since they have higher quadratic losses than others with similar –log(exchange ratio) values, but these are not associated with the most robust design points.

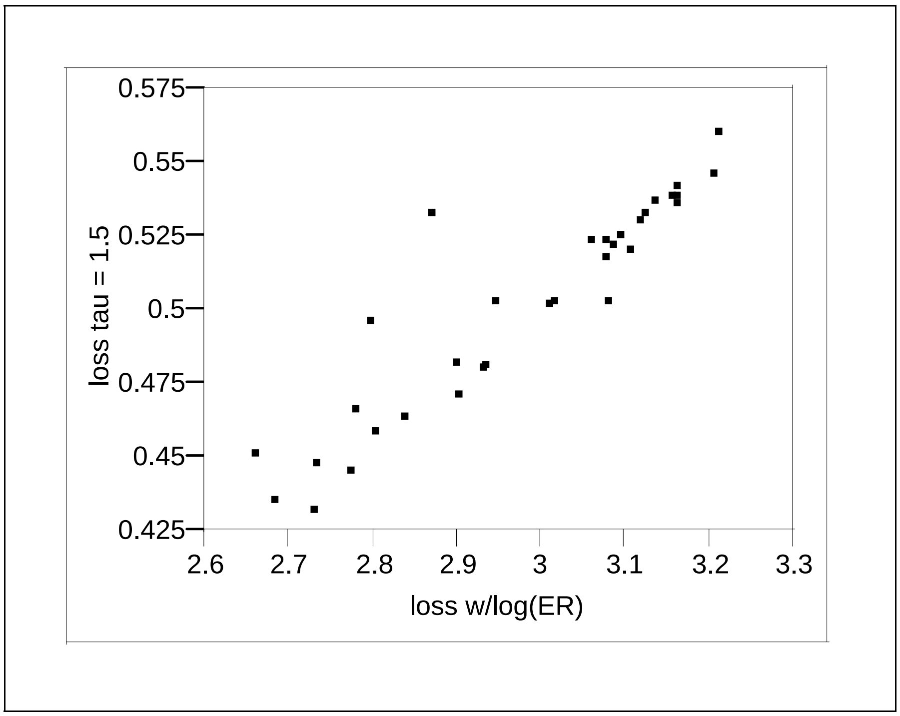


Figure 26.   Loss Function Comparison

E. ROBUSTNESS REVISITED

Recall from the beginning of the chapter that we developed a decision tree using only the decision factors taken over the noise space. Now let us construct a new decision tree using all of the decision and noise factors using loss as our response instead of the exchange ratio. We can see from Figure 27 that similar splits occur.

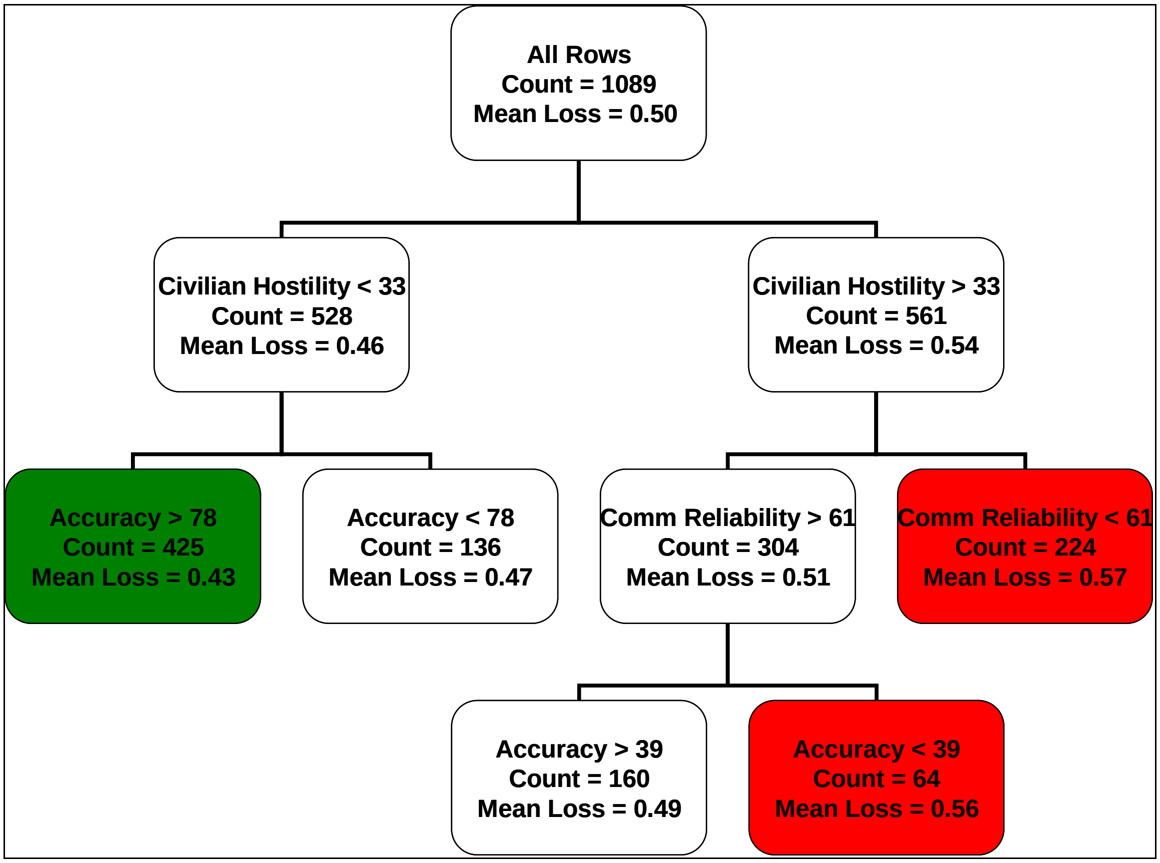


Figure 27. Regression Tree, All Factors.

The regression tree in Figure 27 represents all 1089 design points and considers noise and decision factors together. The overall mean is shown in the top box and the tree has an R^2 of .24. The boxes colored red and green at the bottom of the tree represent the less and more favorable conditions, respectively. For instance, according to the regression tree, if we were in a situation were the civilian hostilities were high, it would be desirable that our communication and accuracy also be high.

The biggest factor impacting the mean loss is the influence on the civilian population by the red forces, or civilian hostility. When the factor setting is greater than 33 the mean loss is .54, if it is less than 33 the loss falls to .46. Remember the influence ranged between 10 and 50, so a value of 33 would represent an area with just above 50% hostile civilians. Depending on the level of hostility by the civilian population, communication reliability and information accuracy are the second most important factors on the tree. If the patrol is operating in an environment with high civilian hostility, greater communication reliability and information accuracy are both needed in order to avoid high loss. Alternately if the civilian hostilities are low, high information accuracy is the most important contributor to low loss.

The regression tree also gives us an idea of the potential trade space given that we possess certain kinds of intelligence. For instance, looking at the regression tree we see that in situations where the local populace is relatively friendly to our forces, we might be able to achieve acceptable results even with a UAV that has low communication reliability and low accuracy.

F. SUMMARY

In this chapter we developed models for the mean exchange ratio, as well as the variance of the exchange ratio. The mean exchange ratio model consisted of seven terms that explained 91% of the variability, with three of these terms explaining 74% of the variability. The ln(variance) model consisted of 8 terms explaining 84% of the variability. Using these two models and the loss function, we developed insights into the best model based on a specific as well as a range of target values. We also developed regression trees for an initial and nonparametric understanding of our data set.

Recall that the goal of this thesis is to provide insights, rather than numbers, so our numerical results should be viewed in this light. The final chapter will link the observations from the statistical analysis with possible implications for the real world.

IV. CONCLUSIONS AND RECOMMENDATIONS

Recall that the purpose of this thesis was to gain insights to small unit urban patrolling with the VTUAV using agent based simulation. We now summarize our findings and provide recommendations for follow-on research.

A. SUMMARY

The metamodels and designs developed for the agent based simulation of this thesis do not translate literally into the real world of modern combat, nor is this the purpose of agent based distillations. What we have been able to observe using these models gives us insights into the potential tactics, techniques, and capabilities that might be important in similar situations. It also provides insights into the possible trade space of technology and asset support given the constant battle over limited resources. This thesis also provides a template for studying other scenarios using robust design.

As stated in the ORD for the VTUAV, it must be able to accomplish missions ranging from MOOTW to a large intensity conflict. Because it must be able to operate in different environments at different levels of conflict, the VTUAV cannot be specifically designed for just one type of operation. Given this requirement, this study focused on a scenario with a broad range of environmental noise factors and intensity levels in order to generate a robust system capable of operating in different environments.

A platform that has very reliable communication capability and very accurate sensing capability is best suited for the environment modeled. These two factors were the most dominant in providing favorable results. A UAV with high reliability and accuracy needs only a relatively narrow field of view to provide favorable results for small units operating in dense urban environments. Speed, as might have been guessed, will probably not play an important role for a UAV in an urban environment. These factors might suggest possible flexibility when using UAVs in support of urban operations. Because of its broad range of required capabilities, the VTUAV will be a very capable, expensive and limited asset. If other, less expensive assets can be used, cost savings and flexibility could be realized. As mentioned in the introductory chapter, the Marine Corps currently possesses the Dragon Eye UAV. Although a slow and rather unsophisticated over-the-hill reconnaissance asset, upgrading its sensing capabilities might make the Dragon Eye a low cost alternative to using the VTUAV in the urban environment.

By introducing noise into the system and using the tool of regression trees, we are given an idea about the potential trade space of required capabilities given our knowledge of certain conditions. For instance, we saw that the hostility of the civilian population plays an important role in urban combat. If civilian hostilities are high, a more sophisticated UAV appears to be necessary for the patrol to operate effectively. In environments with more friendly populations, the Dragon Eye or other less sophisticated intelligence assets might be sufficient to accomplish the mission.

We see from the metamodels and the loss function analysis that the intelligence gathered from the UAV is only a piece of the puzzle. How the blue force uses that intelligence is the other piece. The aggressiveness of the blue force has an impact on the mean exchange ratio. If higher ratios are to be achieved in this model, the blue force must be more aggressive. With increased aggressiveness comes higher variance, resulting in higher rewards but also higher risks. In situations were commanders cannot tolerate the possibility of high losses, a less aggressive force that relies more heavily on the UAV for situational awareness and enemy engagements might be more appropriate.

B. RECOMMENDATIONS FOR FUTURE RESEARCH

Because no two combat situations are alike, the possible variations of combat that one can attempt to model are infinite. This analysis was meant to provide insights, but with those insights comes more questions. Listed below are just a few of the potential areas of future research stemming from this scenario:

- This model uses only one UAV due to its small area of operations. What would be the impact of using other intelligence-gathering devices, such as unmanned ground vehicles and fixed position sensors, in conjunction with the UAV?
- The UAV in this scenario is invulnerable to enemy fire and is assumed to be always operational. While statistics show that the downing of UAVs is rare, the slow speeds required in urban environments might make it more likely to be shot down. How would this vulnerability affect the results?
- What would be the effect of limiting the time on station of the UAV due to endurance limitations or competing requirements from other units?

- This model assumes fairly strict ROE and therefore does not take into account the combined arms capability of our forces. How would modeling this capability affect the outcome?
- This model looked at only one performance measure, the exchange ratio. Future studies might include other performance measures involving civilian casualties or time to complete the mission.
- Other loss functions may be better suited for combat analysis. Any future work using robust design should consider using a loss function that is the most appropriate for the MOE being considered.

With a little imagination the list of variations is virtually endless. This thesis provides some preliminary insights into the capabilities the VTUAV should possess. Other questions will arise over the next few years as the VTUAV is developed and fielded. Once its capabilities are fully known, the research focus can turn to the best ways to employ this new asset.

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX. FINAL REGRESSION MODELS SUMMARY STATISTICS

A. MEAN EXCHANGE RATIO MODEL

Summary of Fit

RSquare	0.912113
RSquare Adj	0.891832
Root Mean Square Error	0.021783
Mean of Response	0.908221
Observations (or Sum Wgts)	33

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	6	0.12804066	0.021340	44.9725
Error	26	0.01233737	0.000475	Prob > F
C. Total	32	0.14037803		<.0001

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.7597702	0.014026	54.17	<.0001
UAV Sweep Width	0.0000713	0.000053	1.34	0.1904
UAV CommReliability	0.0015703	0.000136	11.57	<.0001
UAV InfoAccuracy	0.0012232	0.000136	9.01	<.0001
BlueAggresiveness	0.0014883	0.000348	4.28	0.0002
(UAV CommReliability-50.0606)*(UAV InfoAccuracy-50.0606)	0.0000218	0.000005	4.41	0.0002
(UAV Sweep Width-135.061)*(UAV Sweep Width-135.061)	-0.000004	8.651e-7	-4.43	0.0001

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
UAV Sweep Width	1	1	0.00085761	1.8073	0.1904
UAV CommReliability	1	1	0.06349981	133.8206	<.0001
UAV InfoAccuracy	1	1	0.03852984	81.1985	<.0001
BlueAggresiveness	1	1	0.00868285	18.2984	0.0002
UAV CommReliability*UAV InfoAccuracy	1	1	0.00921669	19.4234	0.0002
UAV Sweep Width*UAV Sweep Width	1	1	0.00933128	19.6649	0.0001

B. LN(VARIANCE) EXCHANGE RATIO MODEL

Summary of Fit

RSquare	0.848906
RSquare Adj	0.8066
Root Mean Square Error	0.136172
Mean of Response	-1.95967
Observations (or Sum Wgts)	33

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	7	2.6045342	0.372076	20.0657
Error	25	0.4635717	0.018543	Prob > F
C. Total	32	3.0681059		<.0001

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-2.500952	0.09381	-26.66	<.0001
UAV Sweep Width	0.0005978	0.000331	1.80	0.0834
UAV CommReliability	0.0067098	0.000849	7.91	<.0001
UAV InfoAccuracy	0.0053155	0.000849	6.26	<.0001
BlueAggresiveness	0.0061833	0.002175	2.84	0.0088
(UAV Sweep Width-135.061)*(UAV InfoAccuracy-50.0606)	0.0000303	0.000014	2.13	0.0433
(UAV Sweep Width-135.061)*(UAV Sweep Width-135.061)	-0.000023	0.000005	-4.25	0.0003
(UAV CommReliability-50.0606)*(UAV CommReliability-50.0606)	-0.00013	0.000041	-3.16	0.0041

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
UAV Sweep Width	1	1	0.0603143	3.2527	0.0834
UAV CommReliability	1	1	1.1594423	62.5277	<.0001
UAV InfoAccuracy	1	1	0.7276172	39.2397	<.0001
BlueAggresiveness	1	1	0.1498617	8.0819	0.0088
UAV Sweep Width*UAV InfoAccuracy	1	1	0.0840276	4.5315	0.0433
UAV Sweep Width*UAV Sweep Width	1	1	0.3347629	18.0535	0.0003
UAV CommReliability*UAV CommReliability	1	1	0.1846960	9.9605	0.0041

LIST OF REFERENCES

Cioppa, Thomas M., Lloyd P. Brown, Leroy Jackson, Dieter Mueller, John Allison, 2003. Military Operations in Urban Terrain Excursions and Analysis with Agent Based Models, in *Maneuver Warfare Science 2003*, 39-47. USMC Project Albert, Quantico, VA.

Cioppa, Thomas M., 2002. *Efficient Nearly Orthogonal and Space-Filling Experimental Designs for High-Dimensional Complex Models*. PhD. Dissertation, Operations Research Department, Naval Postgraduate School, Monterey, CA.

Devore, Jay L., 2000. *Probability and Statistics for Engineering and the Sciences*, 5th Edition. Duxbury Press, Belmont, CA.

Galligan, David P., Mark A. Anderson, Michael K. Lauren, 2004. *Map Aware, Non-Uniform Automata version 3.0.* Defence Technology Agency, Devonport Naval Base, Auckland, New Zealand.

Hamilton, Lawrence C., 1992. *Regression with Graphics: A Second Course in Applied Statistics*. Duxbury Press, Belmont, CA.

Hakola, Matthew B., 2004. *An Exploratory Analysis of Convoy Protection Using Agent-Based Simulation*. M.S. Thesis, Naval Postgraduate School, Monterey, CA.

JMP® Statistics and Graphics Guide, Version 5, SAS Institute Inc., 2002.

Joint Publication 1-02, *Department of Defense Dictionary of Military and Associated Terms*, 12 April 2001.

Kaplan, Fred, *Eyes Over Baghdad, Our secret street-fighting weapon*, 7 April 2003. MSN's *Slate.* Available online at http://slate.msn.com/id/2081236/ [accessed 21 September 2004].

Klein, Larry (Producer/Director). (2002, November). *NOVA: Spies That Fly* [Television broadcast]. WGBH Educational Foundation Boston, MA: Public Broadcasting Service.

Lamont, R. W., 1999. *Armor Evens the Odds in Two Urban Battles A Tale of Two Cities—Hue and Khorramshahr*. The MOUT Homepage, May-June. Available online at http://www.specialoperations.com/mout/twocities.html [accessed 3 September 2004].

Lubold, Gordon, 2004. *Tale of Two Cities*, Marine Corps Times, July 26, 2004 pp. 14-16.

Lucas, Thomas W, Susan M. Sanchez, Lloyd Brown, and William Vinyard, 2002. Better Designs for High-Dimensional Explorations of Distillations, in *Maneuver Warfare Science 2002*, 17-46. USMC Project Albert, Quantico, VA.

Marine Corps Warfighting Publication (MCWP) 3.35.3, *Marine Operations on Urbanized Terrain (MOUT)*, 26 April 1998.

Office of the Secretary of Defense, *Unmanned Aerial Vehicles Roadmap 2002-2027*, December 2002.

Operational Requirements Document (ORD) for the Vertical Takeoff and Landing Tactical Unmanned Aerial Vehicle (VTUAV).

Project Albert Description, retrieved 19 July 2004 from the World Wide Web at http://www.mcwl.quantico.usmc.mil/divisions/DivisionDescription.cfm?ID=23.

Sanchez, S. M. (2004) Excel Spreadsheet for Generating Nearly Orthogonal Latin Hypercube Designs. Available online at http://diana.gl.nps.navy.mil/~susan/SeedLab/ [accessed 21 August 2004].

Sanchez, Susan M., Paul J. Sanchez, John S. Ramberg, and Farhad Moeeni, 1996. Effective Engineering Design through Simulation. *International Transactions on Operational Research* 3, 169-185.

Spies That Fly, NOVA, retrieved 19 July 2004 from the World Wide Web at http://www.pbs.org/wgbh/nova/spiesfly/.

SPMAGTF(X) MOUT Training Program of Instruction/MOUT Homepage, Retrieved from the World Wide Web at http://www.geocities.com/Pentagon/6453/moutpoitdg.html.

United States Department of the Army Field Manual (FM) 3.06.11, *Combined Arms Operations in Urban Terrain*. Washington, D.C., 28 February 2002.

United States Department of the Army Field Manual (FM) 90-10, *Military Operations on Urban Terrain (MOUT)*. Washington, D.C., 15 August 1979.

THIS PAGE INTENTIONALLY LEFT BLANK

INITIAL DISTRIBUTION LIST

1. Defense Technical Information Center
   Ft. Belvoir, Virginia

2. Dudley Knox Library
   Naval Postgraduate School
   Monterey, California

3. Marine Corps Representative
   Naval Postgraduate School
   Monterey, California

4. Director, Training and Education, MCCDC, Code C46
   Quantico, Virginia

5. Director, Marine Corps Research Center, MCCDC, Code C40RC
   Quantico, Virginia

6. Marine Corps Tactical Systems Support Activity (Attn: Operations Officer)
   Camp Pendleton, California

7. Director, Studies and Analysis Division, MCCDC, Code C45
   Quantico, Virginia

8. Professor Susan Sanchez
   Department of Operations Research
   Naval Postgraduate School
   Monterey, California

9. Professor Paul Sanchez
   Department of Operations Research
   Naval Postgraduate School
   Monterey, California

10. Professor David Schrady
    Department of Operations Research
    Naval Postgraduate School
    Monterey, California

11. Dr. Gary E. Horne
    Marine Corps Warfighting Lab
    Quantico, Virginia

12. Major John Giscard
Marine Corps Warfighting Lab
Quantico, Virginia

13. Lieutenant Commander Russell Gottfried
Naval Postgraduate School
Monterey, California

14. Captain Roman Cason
Naval Postgraduate School
Monterey, California